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# Prediction of Compressive Strength of Self-Compacting Concrete (SCC) with Silica Fume Using Neural Networks Models

Mahmoud Serraye [1], Said Kenai [1*], Bakhta Boukhatem [2]

*[1] Geometrical Laboratory, Department of Civil Engineering, University of Blida 1, Ouled Yaïch, Algeria.*

*[2] Department of Civil Engineering, University of Sherbrooke, Quebec, Canada.*

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**Abstract**

Self-Compacting Concrete (SCC) is a relatively new type of concrete with high workability, high volume of paste and containing cement replacement materials such as slag, natural pozzolana and silica fume. Cement replacement materials provide a wide variety of benefits such as lower cost, reduced consumption of natural resources, reduced carbon dioxide emissions and improved fresh and hardened properties. SCC is used in many applications such as sections with congested reinforcement and high rise shear walls and there is a need for the prediction of the performance of SCC used. Artificial Neural networks (ANN) are widely used in civil engineering for the prediction of the performance of some engineering materials such as compressive strength and durability. However, currently, studies on SCC containing silica fume are very rare. In this paper, an artificial neural networks (ANN) model is developed to predict the compressive strength of SCC with silica fume using the Levenberg-Marquardt back propagation algorithm based on a database from 366 experimental studies. The model developed was correlated with a nonlinear relationship between the constituents (input) and the compressive strength of SCC (output). To evaluate the predictive ability and generalize the developed model, other researchers' experimental results were compared with the model prediction and good agreements are found. A parametric study was conducted to study the sensitivity of the ANN proposed model to some parameters such as water/binder ratio and superplasticizer content. The model developed in this study can potentially be used for SCC compressive strength prediction with very acceptable results and a high correlation coefficient $R^2$=0.93. The developed model is practical, easy to use and user friendly.

*Keywords:* Self-compacting Concrete; Silica Fume; Prediction; Compressive Strength; Artificial Neural Networks.

## 1. Introduction

Concrete is the most used material worldwide in civil engineering structures because of its many advantages such as ease of molding, availability of constituent materials, high compressive strength and durability if well designed [1]. Self-Compacting Concrete (SCC) as a relatively new type of concrete has excellent deformability and passing ability under its own weight without any segregation. SCC differs from conventional concrete by its high fines content, high workability and higher water requirements and hence the prediction of its compressive strength is different than that of conventional concrete. Since its development in Japan in the late 1980's, significant progress has been made in SCC research and development. SCC is a solution to enhance the concrete workability as well as its strength. Mechanical properties, such as compressive strength, require selection of blend ratios, blend design specifications and economics

* Corresponding author: sdkenai@yahoo.com

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of the cementitious materials used [2]. Compressive strength of concrete is widely used for the quality control of concrete on site. Compressive strength is generally obtained by testing concrete specimen after a standard curing of 28 days (Neville 1996).This property can be influenced by the use of alternative cementitious materials in concrete [3].

The use of supplementary cementitious materials (SCM) such as slag, natural pozzolana, fly ash (FA) and silica fume (SF) in the production of SCC is gaining widespread as it provides greater sustainability in construction projects by reducing $CO_2$ emission and reducing energy and cement consumption and hence lowering its environmental impact [4]. In addition, SCM improve the rheological properties at the fresh state and the strength and durability at the hardened state at long term. Silica fume is composed of very fine vitreous particles, which is a by-product of the smelting process in the silicon and ferrosilicon industry and is one of the most available SCM [5, 6]. The use of SF can produce both chemical and physical effects, which cause meaningful changes in the micro-structure of concrete such as reducing its permeability and increasing its compressive strength [5]. Compressive strength of SCC and other types of concrete with different cement replacement materials have been widely investigated. The compressive strength of SCC with silica fume and fly ash at different curing regimes was reported and the need for long term water curing proved [7]. Fly ash and slag have been found to significantly increase the compressive strength of SCC mixtures and that the presence of mineral admixtures improves the resistance to sulphate attack [8].

The compressive strength of SCC is a highly nonlinear function of the proportions its ingredients and there are no theoretical relationships between mixture proportioning and SCC strength and hence the need to use appropriate tools for their prediction based on its constituents at the time of design. Artificial neural network could be a good tool for this prediction. Artificial Neural Networks (ANN) is soft computing techniques developed to mimic the neural system of human being in learning from training patterns or data [9]. ANN modelling is getting more popular and has been commonly used in engineering tasks. ANN models can provide more accurate predictions of concrete properties and at the same time reduce the experimental work at the laboratory and on site. The main advantage of ANN is that no specific equation is needed as it relies only on the learning of input–output relation for any complex problem. The technique of neural networks automatically manages the relationships between variables and adapts its parameters based on the data used for their training [10]. This potential of ANN has been harnessed for wide applications in the field of civil engineering. ANN was used to estimate the main parameters needed in the design of concrete such as the compressive strength of hydrated lime cement concrete [11]. ANN was also used to evaluate the sulphate expansion of different types of cement using water/binder, cement content, FA or SF, $C_3A$, and exposure duration as input parameters [12]. Compressive strength and other properties of limestone filler concrete were also predicted using ANN modelling [7]. The concrete mix design incorporating natural pozzolans has also been modelled [13]. ANN models for some durability indicators such as carbonation depth and other properties of fly ash ordinary concrete and SCC was also studied [14, 15].

Many authors have proved that artificial neural networks are reliable computational models for the prediction of concrete strength. Saridemir [16]. Siddique et al. [17] developed an ANN model for a reasonable accurate predictions of the compressive strength of concrete with bottom ash as partial replacement of fine aggregates at different ages using eight input parameters. Chou and Fam [18] reported that combining two or more models produces the highest prediction performance of compressive strength of high performance concrete (HPC). It has been demonstrated that artificial neural networks and fuzzy logic approaches can be successfully used for the prediction of compressive strength of concrete with metakaolin in relatively short time and with little error rate. The 28 days compressive strength of no-slump concrete (NSC) was predicted using neural networks and found more feasible than the traditional regression models [19]. Neural network and fuzzy logic have also been proved as an alternative approach for the predicting of compressive strength of silica fume concrete [20]. ANN was also used to predict with reasonable accuracy the 28-days compressive strength of a normal and high strength SCC as well as high performance concrete (HPC) containing high volume fly ash over a wide range of compressive strengths of concrete from about 30 to 60 MPa [21].

Early evaluation of the compressive strength of SCC is important for design and application purposes in construction sites and ready mixed concrete plants. As strength is usually determined experimentally by destructive and non-destructive tests which are costly and time consuming, the prediction of compressive strength through mixture proportions by an ANN model can be useful for the concrete industry. Some work has been done for the prediction of the compressive strength of SCC but although SF is extensively used in SCC and ultra-high performance concrete, there are very limited investigations to predict the compressive strength from its constituents for SCC with SF.

The aim of this investigation is to develop a user friendly ANN model for predicting the compressive strength of SCC incorporating silica fume. After a brief description of the neural network model used, the database collection and analysis was described. Then, the training of the ANN model was carried out on a set of experimental data considering several parameters such as water/binder ratio, binder content, silica fume, sand content (S), gravel content (G), superplasticizer (Sp) and curing age (A). These parameters were used as experimental input variables while the experimental compressive strength (CS) property was used as an output. The validity of the model was then checked. Finally, a parametric analysis and comparison were carried out between the experimental and the ANNs predicted results for performance evaluation of the ANNs model.

## 2. Description of Neural Network Models

ANN is a very powerful computational tool for modelling complex non-linear relationships inspired by biological neural networks [10]. There is an increasing number of different types of ANN and learning algorithms such as deep learning with convolutional neural networks [22] and the most used and well-known training algorithms for the multilayer perceptron is the back-propagation multi-layer perceptron (BPMLP). The technique is based on a gradient descent technique. It is used for minimizing the error for a particular training pattern by adjusting the weights by a small amount at a time [15, 23]. This technique is widely used in civil engineering applications [15]. In a BPMLP, the arrangement of neurons or nodes is in the form of one input layer, one output layer and hidden layers. All the neurons in each layer have connections to all the neurons in the next layer as depicted in Figure1.

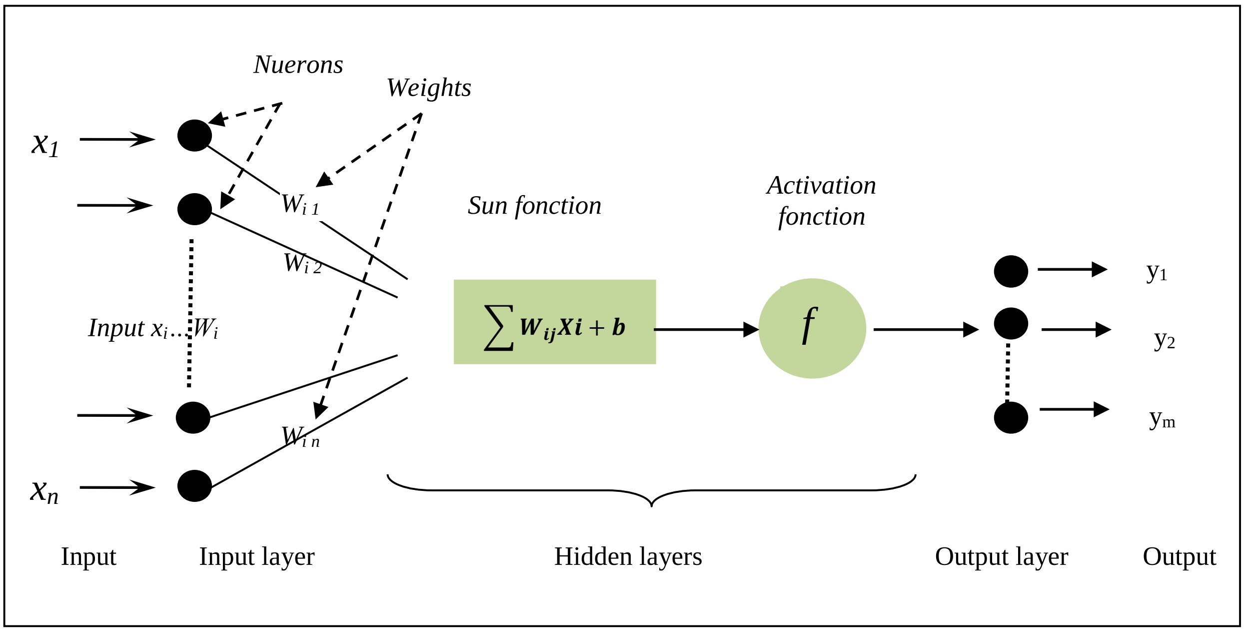



**Figure 1. Typical neural network architecture**

At each neuron, the weights are values that express how much effect the input will have on the output. The total number of nodes in the input and output layers represent the number of input and output variables. The ideal number of nodes in the hidden layer is determined by trial and error as there is no known rule for selecting the number of nodes in a hidden layer, which is a network dependent [15]. The activation function determines the output value of each neuron. A non-linear activation function is generally used for all neurons with full connection that maps the weighted inputs to the output of each neuron. Two non-linear sigmoid activation functions are used as presented in Figure1 [16, 23].

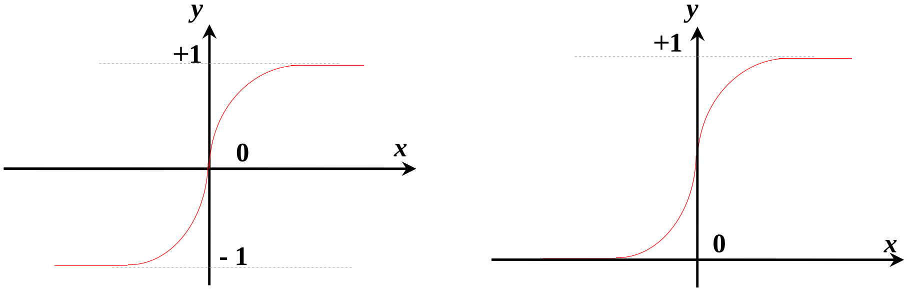



**Figure 2. Tan-Sigmoid and logistic Transfer function**

The first is a hyperbolic tangent function that ranges from -1 to 1, while the second is a logistic, with similar shape but ranges from 0 to 1. The output of the neuron is y and x is the weighted sum of the input connections. To train the network, a training algorithm is used allowing the ANN to develop a relationship between the inputs and outputs [23]. The training is an iterative process that stops when a designed error is reached by adjusting the network weights. The training related parameters such as the learning rate, momentum and stopping time are the most important parameters that should be selected during the training in order to increase the model speed convergence and prevent it from over fitting.

The network performance is determined by the root mean square error (RMSE) and the absolute fraction of variance (R2) using respectively Equations 1 and 2. In addition, Equation 3 determines the mean absolute percentage error (MAPE):

$$RMSE = \sqrt{MSE} = \sqrt{\left(\frac{1}{P}\right) * \sum_j (t_j - o_j)^2} \tag{1}$$

$$R^2 = 1 - \left( \frac{\sum_j (t_j - o_j)^2}{\sum_j (o_j)^2} \right) \tag{2}$$

$$MAPE = \frac{1}{P} \sum_j \left( \left| \frac{o_j - t_j}{o_j} \right| 100 \right) \tag{3}$$

Where $t_j$ is the target value of jth pattern (corresponds to predicted result in this work), $o_j$ is the output value of jth pattern (corresponds to experimental results in this work), and P is the number of patterns. The network is able to give the output for any other input not included in the database when the training process is complete [23].

## 3. ANN-based Prediction Model of SCC Compressive Strength and Validation

The main purpose of this study is to develop ANN models for predicting the compressive strength based on mixture proportioning of SCC with SF. The development process of this ANN model was divided into three main sections. The first section concerns the collection and analysis of data on SCC with silica fume. The second is devoted to selecting suitable ANN architectures and optimal training parameters including performance function, learning algorithm and execution time. In the third and last section, a comparison with other existing experimental data was carried out to validate the proposed ANN models and assess their performances. The research methodology is summarized in Figure 1.

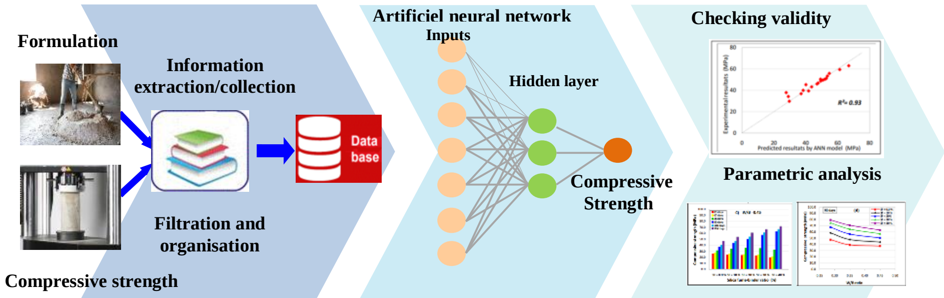



**Figure 3. Flowchart of research methodology**

### 3.1. Database Collection and Analysis

The database of compressive strengths of SCC with SF was assembled from different research projects. A total number of 366 SCC compositions (Table 5) were collected from 25 sources published between 2004 and 2020 (Figure 4) for building the ANN model (training testing and checking).

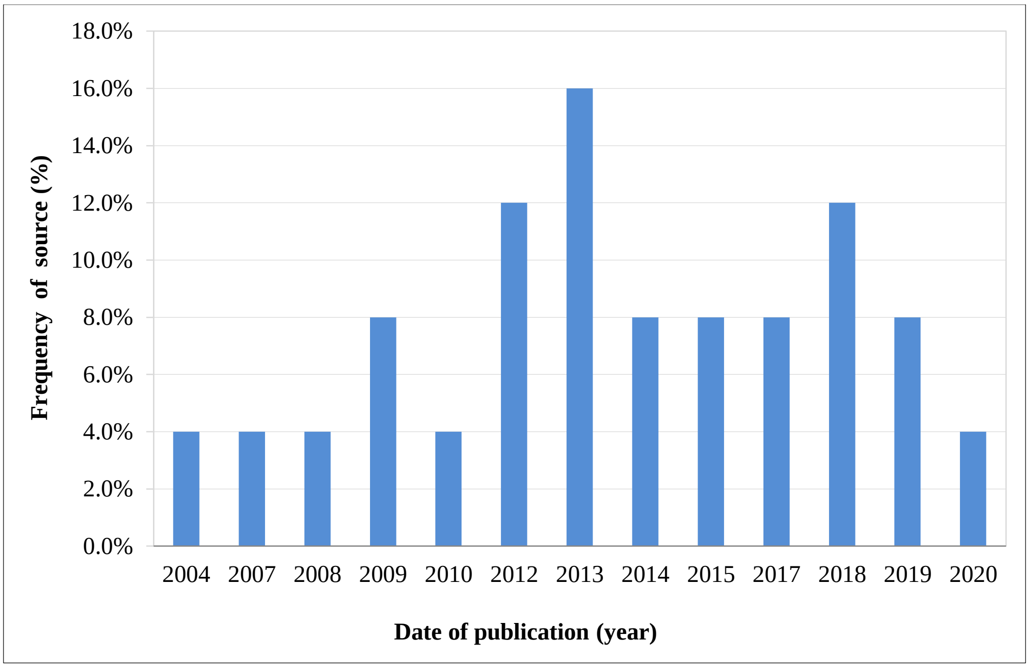



**Figure 4. Frequency of sources in different date of publication**

During the evaluation and selection of the data, some of the mixes were ignored due to inaccurate or insufficient information or due to special curing conditions and larger than 20 mm size aggregates. The variables of the data base are quantities for one cubic meter of concrete mix constituents (binder content, silica fume, fine aggregates, coarse aggregates, superplasticizer) and age of testing as input dataset with the corresponding compressive strength value at different ages as output dataset. The compressive strengths tests were performed on cubic specimens of (10×10×10) cm and (15×15×15) cm, and cylindrical specimens of (10×20) cm and (15x30) cm. All of compressive strength results were converted into equivalent 15x30 cylindrical using the following empirical formulas (Equations 4 and 5) [24].

$$f_\alpha = f_{10}\left[0.58 + 0.42\left(\frac{10}{\alpha}\right)^{1/3}\right] \tag{4}$$

$$f_{cyl} = f_{15}\left[0.76 + 0.2\log_{10}\left(\frac{0.95 f_{10}}{19.6}\right)^{1/3}\right] \tag{5}$$

Where $f_\alpha$ is the cube compressive strength, α is the cube size, $f_{10}$ and $f_{15}$ are 10 cm and 15 cm cube compressive strength respectively, $f_{cyl}$ is the cylinder compressive strength.

Table 1, shows the boundary values for input and output variables used in the ANN model. Table 2 shows that the input parameters are distributed in different ranges in a homogeneous form for training the mode l.

**Table 1. Boundary range of inputs and output of model**

| | Minimum | Maximum | Average |
|---|---|---|---|
| Inputs variables | | | |
| Water to binder ratio "W/B" | 0.22 | 0.51 | 0.38 |
| Binder "B" (kg/m³) | 359 | 600 | 702 |
| Silica fume (kg/m³) | 0 | 250 | 46 |
| Fine aggregate (kg/m³) | 680 | 1166 | 903 |
| Coarse aggregate (kg/m³) | 595 | 1000 | 817 |
| Superplasticizer (kg/m³) | 1.30 | 15.00 | 7.21 |
| Age of specimen (days) | 1 | 270 | |
| Outputs variable | | | |
| Compressive strength (MPa) | 21.12 | 106.60 | 54.01 |

**Table 2. Distribution of inputs in the data base**

| Water/binder | | Binder | | Silica fume | | Fine aggregate | | Coarse aggregate | | Superplasticizer | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Rang | Freq. | Rang (kg/m³) | Freq. | Rang (kg/m³) | Freq. | Rang (kg/m³) | Freq. | Rang (kg/m³) | Freq. | Rang (kg/m³) | Freq. |
| 0.20-0.25 | 1 | 350–400 | 8 | 0–30 | 43 | 650–750 | 5 | 550–650 | 11 | 0–3 | 7 |
| 0.26–0.30 | 4 | 401–450 | 26 | 31–60 | 29 | 751–850 | 22 | 651–750 | 21 | 3.1–6 | 20 |
| 0.31–0.35 | 17 | 451–500 | 15 | 61–90 | 17 | 851–950 | 48 | 751–850 | 14 | 6.1–9 | 61 |
| 0.36–0.40 | 57 | 501–550 | 43 | 91–120 | 10 | 951–1050 | 14 | 851–950 | 49 | 9.1–12 | 9 |
| 0.41–0.52 | 21 | 551–600 | 8 | 121–250 | 1 | 1051–1166 | 11 | 951–1050 | 5 | 12.1–15 | 3 |

## 3.2. ANN Architectures and Training Parameters

In this research, to provide an ANN model with good generalization capability, the databases were randomly divided into three datasets: 70 % of input values are considered as training, 15 % as validating, and the remaining 15 % as testing. In order to achieve the optimum data division in this study, several random combinations of the training, testing, and validation sets were tried until three consistent datasets were obtained as shown in Table 3.

For conducting ANN model, a MatLab program was implemented using neural network toolbox functions (R2016b). The back-propagation algorithm was employed to train and test the ANN model consisting of three adjacent layers: one input layer, one hidden layer, and one output layer and each layer is composed of a number of neurons. The number of neurons in input and output layers corresponds to variables of data and target output respectively. The number of hidden layers and their size were selected after several attempts in order to achieve the desired result since there is yet no theory or rule for determining the number of hidden layers to construct the network [13]. Subsequently, seven (07) neurons in the input layer representing the variables of data, three (03) neurons in the hidden layer and one (01) neuron in the output layer corresponding to the compressive strength at different ages were selected for the ANN model. The following variables were used as input parameters to build and train the model namely: amount of the water-to-binder ratio (W/B), binder content (B), silica fume (SF), fine aggregates (FA), coarse aggregates (CA), superplasticizer (SP) and age of curing. The corresponding model is given graphically in Figure. 5.

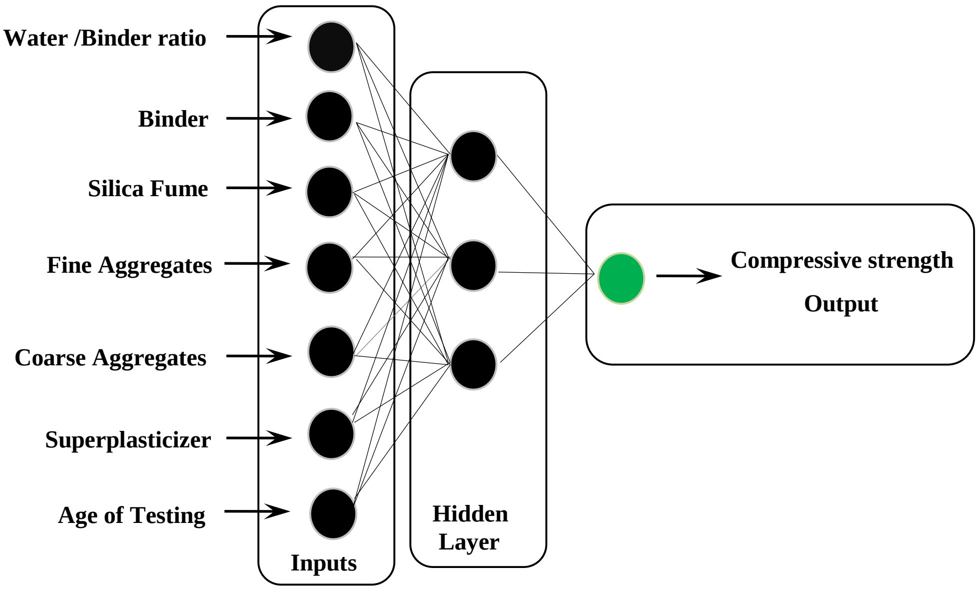



**Figure 5. Structure of the developed ANN model**

After different combinations of the two proposed nonlinear activation function, the nonlinear activation function “tansig” of MATLAB's was used for all neurons as shown in Equation 6.

$$Tanh(y) = \frac{(1 - e^{-2x})}{(1 + e^{-2x})} \tag{6}$$

This function is highly recommended as it is the fastest back propagation algorithm as compared to other algorithms. By minimizing the performance function (mean square error) during the training process, a maximum number of epochs (learning cycles) were reached. All the training parameters for each ANN model including learning rate, momentum rate, training epoch and mean square error are summarized in Table 3.

**Table 3. The values of ANN parameters models used in this research**

| ANNs parameters | |
|---|---|
| Train function | Trainlm (Levenberg–Marquardt) |
| Transfer function | Tansig "tan-sigmoid" (no linear function) |
| Performance function | MSE (mean square error) |
| Train epochs | 1000 |
| Error after learning | 0.001 |
| Divide function | Dividerand |
| Learning rate | 0.100 |
| Momentum rate | 0.001 |
| Goal | 0.001 |
| Show | 5 |

The criterion to select the optimal architecture and the best learning parameters of ANN models developed in this research, involves minimizing the error, maximizing the correlation and conducting a parametric analysis for exploring the most influential factors of SCC mixtures on the ANN model prediction. Accordingly, the prediction results are compared with the experimental data showing high correlation and providing high estimation accuracy (Figure. 6).

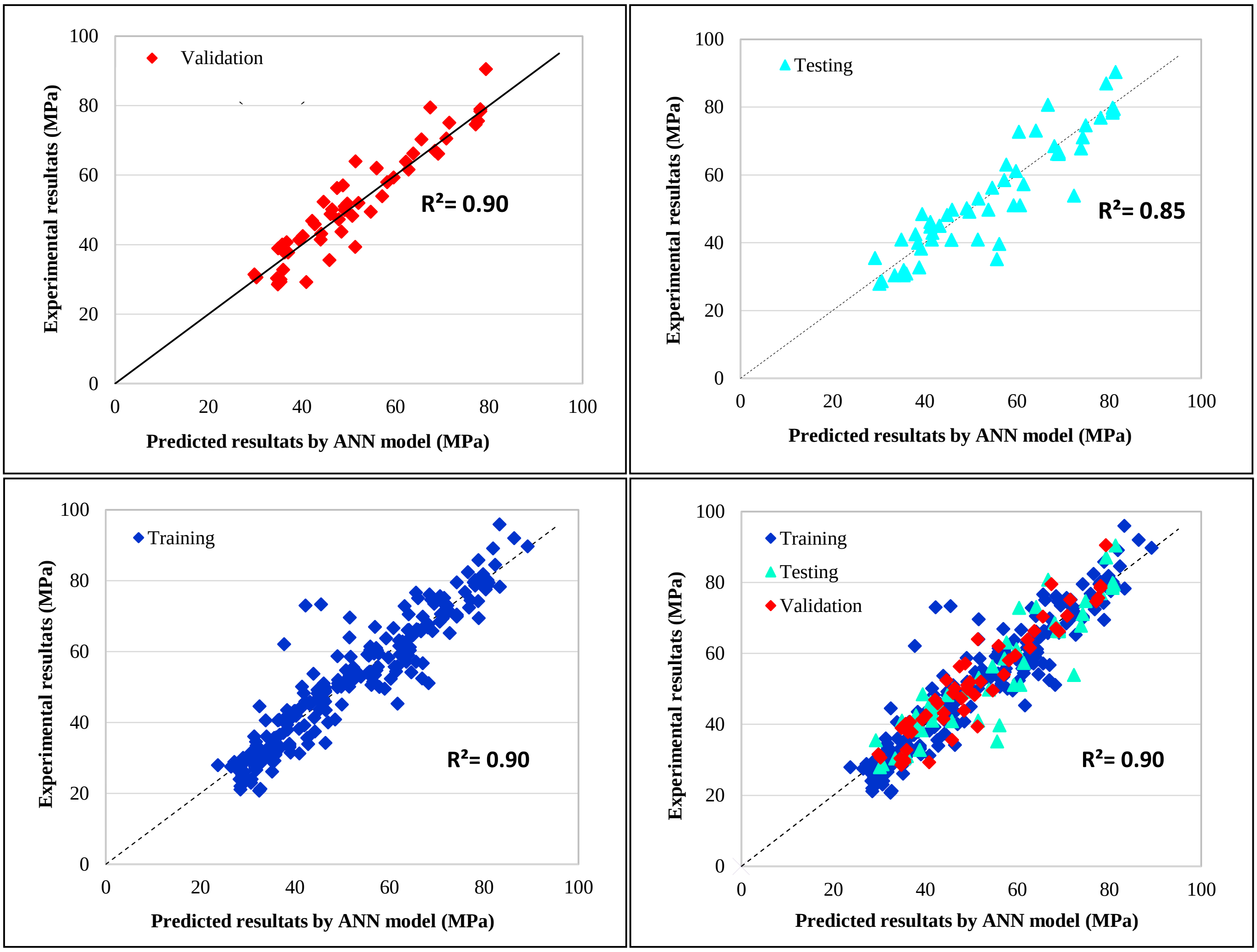



**Figure 6. Correlation cohered between experimental and predicted compressive strength for SCC (a) Validation, (b) Testing set, (c) Training set, (d) All sets**

### 3.3. Checking Validity of the ANN Model

In this section, the generalization performance of the well-trained ANN model was evaluated in order to check its predictive ability and accuracy with unseen data within the range of the input parameters used in the training process. Therefore, additional experimental results obtained from other researchers excluded from the training data were considered. A total of 19 SCC mixtures collected from three different sources [25-27] were presented to the ANN model developed and the network was required to predict the compressive strength associated with each mixture. Moreover, in table 4, the accuracy was measured based on the mean absolute percentage error (E) as a potential solution to improve the interpretability of the results prediction using Equation 7 [25]:

$$E(\%) = ABS\left(\frac{O_{Exp} - O_{ANN}}{O_{Exp}}\right) \times 100 \tag{7}$$

Where $O_{Exp}$ is the experimental result, $O_{ANN}$ is the predicted result calculated by the developed model.

According to table 4, the average relative errors between the predicted and the experimental results were quite low (4.94 %) though slightly higher than that reported for the prediction of compressive strength of concrete with natural pozzolana [23]. From figure 5 and table 4, it can be concluded that the predicted results obtained from the ANNs model are in agreement with those of the measured experimental results.

The comparison between the obtained results by the developed ANN model and the validation of new data records is shown in Figure 6 and in Table 4. According to Figure 7, the testing data points (experimental results) are located along the equity line within the cluster formed by training data points (predicted results), with perfect correlation ($R^2$=0.93).This is comparable to the coefficients of correlation reported for the prediction of the compressive strength of concrete with natural pozzolana which was 0.93 for the hybrid system and 0.83 for the ANN model [23] and for the compressive strength of SCC with fly ash which was 0.95 [15]. A correlation coefficient of 0.919 was achieved for the prediction of 28 days compressive strengths using ANN for SCC containing bottom ash as partial replacement of fine aggregates [17]. Accordingly, the compressive strength of SCC containing silica fume is predicted with very satisfactory results using the proposed ANN model in this research. The results of the developed model are also comparable to other artificial intelligence methods such Multivariate Adaptive Regression Splines (MARS) and Gene Expression Programing (GEP) which were used for the prediction of the compressive strength of SCC with SF using 117 datasets where the comparison between the predicted compressive strength and the experimental results showed a correlation coefficient of 0.98 and 0.83 for MARS and GEP methods respectively [28].

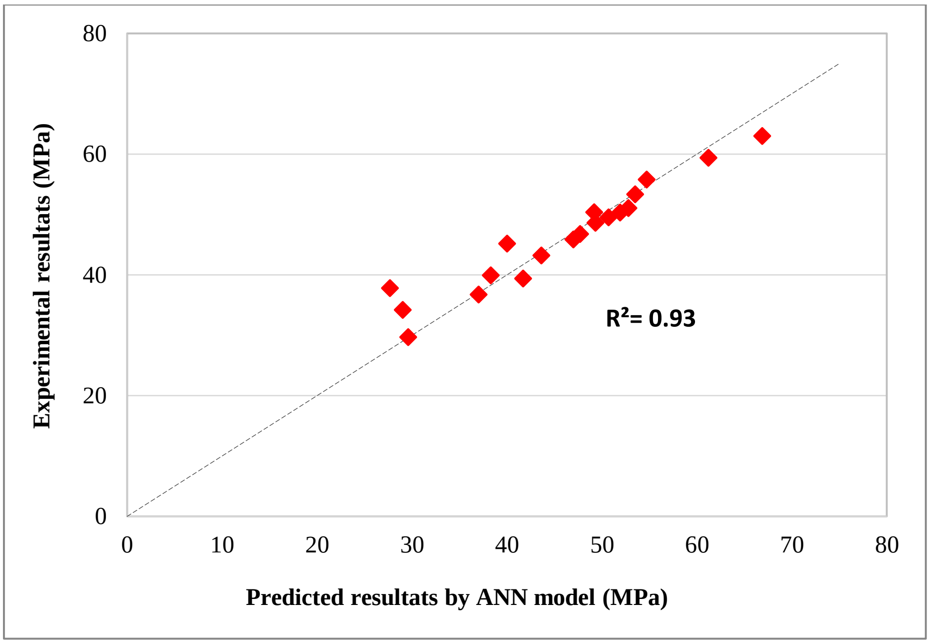



**Figure 7. Comparison between the ANN results and experimental results**

**Table 4. Relative errors of the predicted results of ANN model and experimental researcher's results**

| Author | Year | Age (day) | Exp. | ANN | E (%) |
|---|---|---|---|---|---|
| Tahwia *et al* [25] | 2018 | 7 | 29.70 | 29.60 | 0.34 |
| | | 7 | 34.20 | 29.03 | 15.12 |
| | | 7 | 37.80 | 27.67 | 26.80 |
| | | 28 | 43.20 | 43.61 | 0.95 |
| | | 28 | 45.90 | 47.00 | 2.40 |
| | | 28 | 50.40 | 49.18 | 2.42 |
| | | 90 | 55.80 | 54.72 | 1.94 |
| | | 90 | 59.40 | 61.21 | 3.05 |
| | | 90 | 63.00 | 66.88 | 6.16 |
| Dinesh *et al* [26] | 2017 | 28 | 46.77 | 47.70 | 1.99 |
| | | 28 | 48.62 | 49.30 | 1.40 |
| | | 28 | 49.53 | 50.70 | 2.36 |
| | | 28 | 50.31 | 51.90 | 3.16 |
| | | 28 | 51.05 | 52.80 | 3.43 |
| | | 28 | 53.34 | 53.50 | 0.30 |
| Syed., A. [27] | 2009 | 28 | 36.77 | 37.00 | 0.63 |
| | | 28 | 39.93 | 38.30 | 4.08 |
| | | 28 | 45.20 | 40.00 | 11.50 |
| | | 28 | 39.39 | 41.70 | 5.86 |
| | | | **Average error** | | **4.94%** |

## 4. Parametric Analysis of ANN Developed Model

A parametric study was conducted to evaluate the effect of the operating parameters affecting SCC compressive strength as this allows the developed ANN model to be used as an effective prediction tool. The sensitivity of the compressive strength predicted by the ANN model as output parameters to variations of some of the main input parameters was evaluated by examining the effect of changing one parameter whereas all others were kept constant. Consequently, this yields functional relations between the compressive strength and the other mix design parameters (water-to-binder ratio, amount of binder, silica fume, fine aggregates, coarse aggregates, superplasticizer and curing age) . The simulation results and discussion are shown as follows.

### 4.1. Effect of Water-binder Ratio and SF Content on Compressive Strength at Different Ages

The water-binder (w/b) ratio is the basic parameter that governs the SCC compressive strength. Fig. 8 shows the influence of the w/b (0.30, 0.35 and 0.45) on the compressive strength of SCC with increasing amounts of SF (from 0 to 40%) at different ages (3, 7, 28, 90, 180 and 365 days). As seen from these curves, the values of compressive strength decrease with increasing w/b ratio at all ages with different dosages of SF. A similar trend was reported earlier by other researchers [29-32] in which this negative effect can be explained by an increase of the volume of capillary pores leading to a reduction in compressive strength [33]. On the other hand, at early-age (3 and 7 days), the compressive strength decreases with increasing SF content. The compressive strength of the control SCC (SF = 0.0 %) is always higher than that of SCC with different dosages of SF. Similar results have been reported by other authors [33-35]. The loss of the compressive strength increased from 20 % to 35 % with increasing SF from 0 % to 40 %. This could be caused by the dilution effect resulting from the addition of silica fume and the multiplication of the pseudo crystals of Portlandite. However, the pozzolanic reaction takes place very quickly, and consumes the Portlandite produced by the nucleation hydrogen [35, 36]. As shown in Figures 8 and 9, at the age of 28, 90, 180 and 365 days, the values of compressive strength of all SCC increased with increasing SF content. For example, at 0.35 w/b ratio, when varying SF content from 0 to 40%, compressive strength increases by about 9 to 18% compared to that of control concrete at 90 days. The increase in compressive strength of SF mixtures could be explained by the higher pozzolanic activity of the silica fume [37, 38].

### 4.2. Effects of Superplasticizer on the Compressive Strength

Superplasticizer (SP) is an essential ingredient in the production of the SCC. Although, superplasticizers are added to concrete mainly to provide a better workability by the dispersion of agglomerated cement particles without increasing the water content, they can be used as water reducing admixtures and hence improve the compressive strength and durability of concrete [39]. The variation of the compressive strength at different ages with superplasticizer dosages (from 0 to 9 kg) for different dosage of SF is shown in Figure 10. According to this figure, it should be noted that increasing the content of superplasticizer has a positive effect on compressive strength at all ages, as reported earlier by Neville [40].

## 5. User Interface Development of the ANN Model

Designers in the laboratory or on site need software and computing tools that are more robust and user friendly, for easy applications by non-specialist engineers. In this study, considerable effort and time were devoted to make the model easy to use, user friendly and with visual interface by using the MATLAB based (R2016b). Numerical values of water/binder ratio, amount of binder, silica fume, aggregates, and superplasticizer and the age of test can be entered as shown in Figure 11. The compressive strength of SCC is then displayed directly by clicking the predict button.

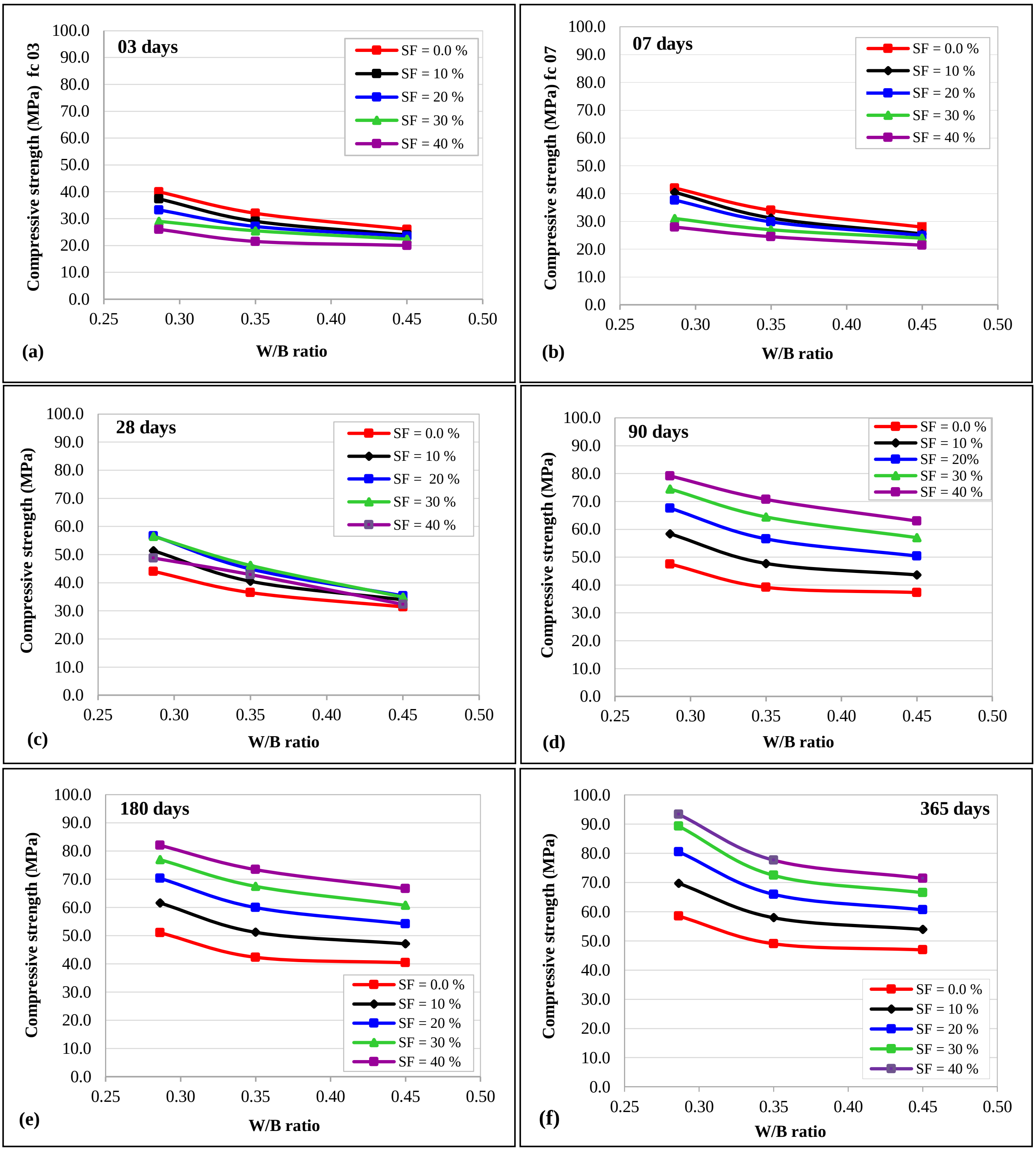



**Figure 8. Effect of w/b ratio on ANN prediction of the compressive strength of SCC with different amounts of SF at various ages of (a) 3 days, (b) 7 days, (c) 28 days, (d) 90 days, (e) 180 days and (f) 365 days**

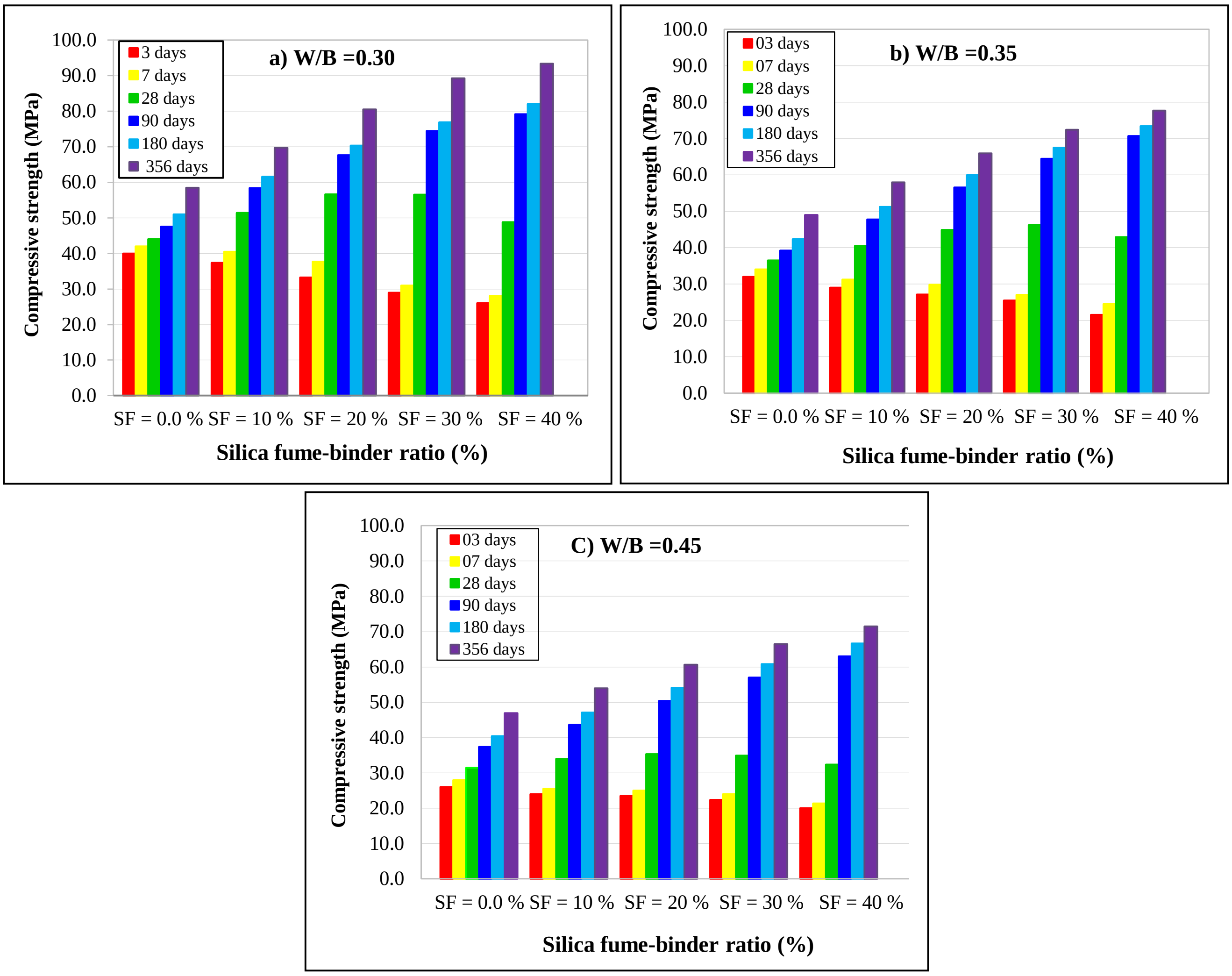
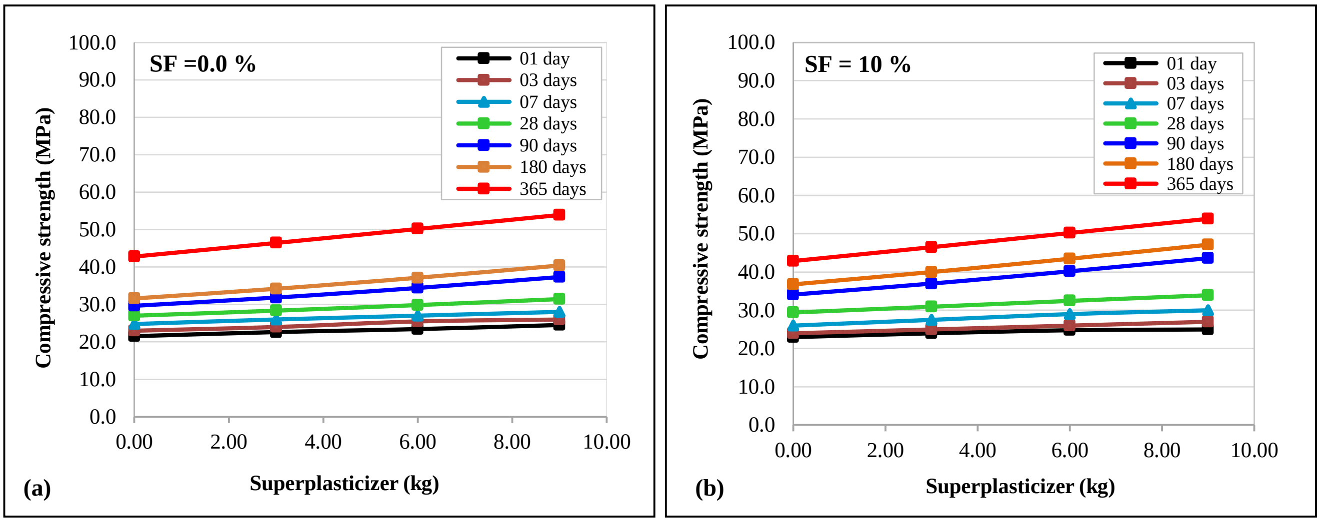



**Figure 9. Effect of age on the compressive strength at different w–b ratios w/b = 0.3, w/b = 0.35, w/b = 0.45**



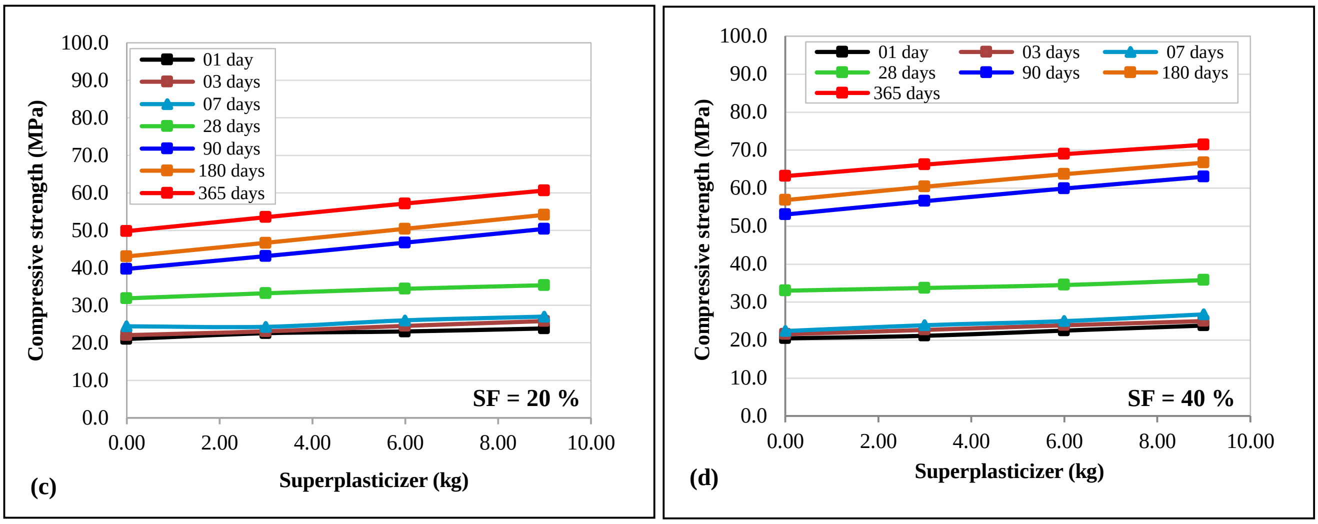



**Figure 10. Effect of superplasticizer content on SCC compressive strength for various ages at SF content of (a) 0.0%, (b) 10%, (c) 30% and (d) 40%**

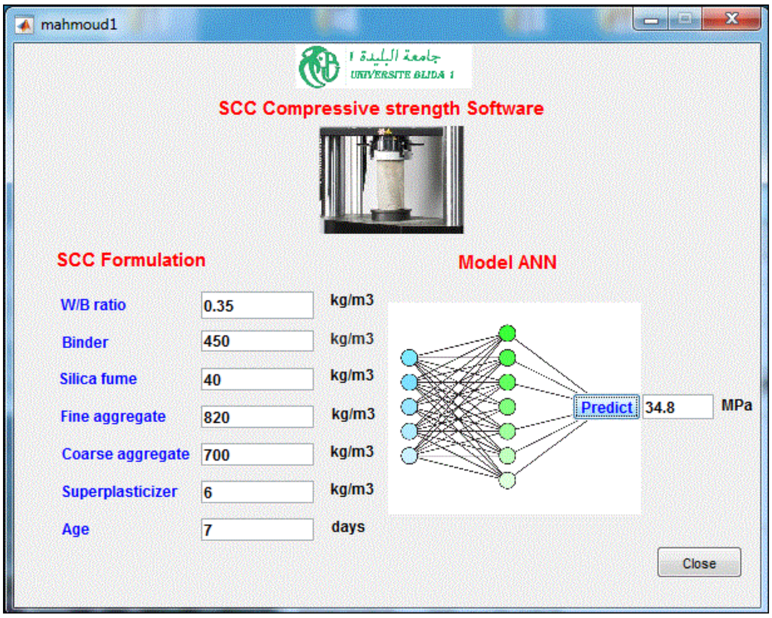



**Figure 11. ANN interactive graphical user interface**

## 6. Conclusions

In this study, an artificial neural network model was built to predict with good accuracy the SCC compressive strength with silica fume as cement replacement material. For this model, feed-forward Backpropagation network trained by Levenberg–Marquardt algorithm was used. The results obtained from this paperled to the following conclusions:

- The SCC compressive strength model based on the ANN using the back-propagation algorithm is more accurate than the model based on other ANN training algorithms. The proposed model gave very acceptable results with a high correlation coefficient $R^2$ equal to 0.93;
- The predicted results coincide well with the experimental values in all phases of training, testing and validation clarifying the accuracy of the proposed ANNs model;
- The developed model was able to evaluate the effect of all SCC constituents (binder, SF content, fine aggregates, coarse aggregates and superplasticizer) as well as water/binder ratio on the compressive strength of SCC with SF. The simulation results are in agreement with previous literature findings;
- The proposed ANN model is a very convenient mix design method that for concrete mix designers to estimate the compressive strength of SCC based only on its constituents at the time of design. The simulation of experiments reduces time and cost;

- An improvement in compressive strength of SCC with the use of SF as a partial replacement of cement is shown based on ANN model. The model prediction results demonstrate that it is feasible to use SF to produce normal strength SCC;
- The developed model is characterized by being practical, accurate, user friendly and easy to use;
- The developed model is limited to SCC with SF and further work is needed to investigate the effect of fiber reinforced SCC as well as the workability (slump flow, the V-funnel time and the L-box ratio), elasticity modulus and durability indicators such as water and oxygen permeability of SCC with silica fume.

# 7. Declarations

## 7.1. Author Contributions

Serraye, M.: Data curation, investigation, writing original draft. Kenai, S.: Conceptualization, supervision, funding acquisition, methodology, formal analysis, validation, writing-review, and editing. Boukhatem, B.: Validation, supervision, writing-review & editing.

## 7.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

## 7.3. Funding

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## 7.4. Conflicts of Interest

The authors declare no conflict of interest.

# 8. References

[1] Mahdikhani, Mahdi, and Ali Akbar Ramezanianpour. "New Methods Development for Evaluation Rheological Properties of Self-Consolidating Mortars." Construction and Building Materials 75 (January 2015): 136–143. doi:10.1016/j.conbuildmat.2014.09.094.

[2] Nuruddin, M. F, Khan, S.U., Shafiq, N. and Ayub, T. "Strength prediction models for PVA fibre reinforced high-strength concrete." Journal of Materials in Civil Engineering 27(12) (March 2015): 2-16. doi:10.1061/(ASCE)MT.1943-5533.0001279.

[3] Ramezanianpour, Ali Akbar. "Cement Replacement Materials." Springer Geochemistry/Mineralogy (2014). doi:10.1007/978-3-642-36721-2.

[4] Ahari, R.S., Erdem, T.K, and Ramyar, K. "Effect of various supplementary cementitious materials on rheological properties of self-consolidating concrete." Construction and Building Materials 75 (November 2014): 89–98. doi:10.1016/j.conbuildmat.2014.11.014.

[5] Tanyildizi, H, and Çevik, A. "Modelling mechanical performance of lightweight concrete containing silica fume exposed to high temperature using genetic programming". Construction and Building Materials 24 (December 2010): 2612–2618. doi:10.1016/j.conbuildmat.2010.05.001.

[6] Paris, Jerry M., Justin G. Roessler, Christopher C. Ferraro, Harvey D. DeFord, and Timothy G. Townsend. "A Review of Waste Products Utilized as Supplements to Portland Cement in Concrete." Journal of Cleaner Production 121 (May 2016): 1–18. doi:10.1016/j.jclepro.2016.02.013.

[7] Bingöl, A. Ferhat, and İlhan Tohumcu. "Effects of Different Curing Regimes on the Compressive Strength Properties of Self Compacting Concrete Incorporating Fly Ash and Silica Fume." Materials & Design 51 (October 2013): 12–18. doi:10.1016/j.matdes.2013.03.106.

[8] Uysal, Mucteba, and Mansur Sumer. "Performance of Self-Compacting Concrete Containing Different Mineral Admixtures." Construction and Building Materials 25, no. 11 (November 2011): 4112–4120. doi:10.1016/j.conbuildmat.2011.04.032.

[9] Ayat, H., Kellouche, Y., Ghrici, M, and Boukhatem, B. "Compressive strength prediction of limestone filler concrete using artificial neural networks". Advances in Computational Design 3(3) (July 2018): 289-302. doi:10.12989/acd.2018.3.3.289.

[10] Tenza-Abril, A.J., Villacampa, Y., Solak, A.M, and Baeza-Brotons, F. "Prediction and sensitivity analysis of compressive strength in segregated lightweight concrete based on artificial neural network using ultrasonic pulse velocity". Construction and Building Materials189 (2018): 1173–1183. doi:10.1016/j.conbuildmat.2018.09.096.

[11] Awodiji, Chioma Temitope Gloria, Davis Ogbonnaya Onwuka, Chinenye Okere, and Owus Ibearugbulem. "Anticipating the Compressive Strength of Hydrated Lime Cement Concrete Using Artificial Neural Network Model." Civil Engineering Journal 4, no. 12 (December 24, 2018): 3005. doi:10.28991/cej-03091216.

[12] Hodhod, Osama, and Gamal A. Salama. "Analysis of Sulfate Resistance in Concrete Based on Artificial Neural Networks and USBR4908-Modeling." Ain Shams Engineering Journal 4, no. 4 (December 2013): 651–660. doi:10.1016/j.asej.2013.02.007.

[13] Boukhatem, Bakhta, R. Rabouh, and M. Ghrici. "Optimizing a concrete mix design incorporating natural pozzolans using artificial neural networks." Computer Concrete 10, no. 6 (2012): 557-573.

[14] Kellouche, Yasmina, Bakhta Boukhatem, Mohamed Ghrici, and Arezki Tagnit-Hamou. "Exploring the Major Factors Affecting Fly-Ash Concrete Carbonation Using Artificial Neural Network." Neural Computing and Applications 31, no. S2 (June 19, 2017): 969–988. doi:10.1007/s00521-017-3052-2.

[15] Douma, O.B., Boukhatem, B., Ghrici, M, and Hamou, A.T. "Prediction of properties of self-compacting concrete containing fly ash using artificial neural network". Neural Computing Applications. 28 (1) (2017): 707-718. doi:10.1007/s00521-016-2368-7.

[16] Sarıdemir, M. "Predicting the compressive strength of mortars containing metakaolin by artificial neural networks and fuzzy logic." Advances in Engineering Software 40 (September 2009): 920–927. doi:10.1016/j.advengsoft.2008.12.008.

[17] Siddique, R., Aggarwal, P, and Aggarwal, Y. "Prediction of compressive strength of self-compacting concrete containing bottom ash using artificial neural networks". Advances in Engineering Software 42 (October 2011) 780–786. doi:10.1016/j.advengsoft.2011.05.016.

[18] Chou, Jui-Sheng, and Anh-Duc Pham. "Enhanced Artificial Intelligence for Ensemble Approach to Predicting High Performance Concrete Compressive Strength." Construction and Building Materials 49 (December 2013): 554–563. doi:10.1016/j.conbuildmat.2013.08.078.

[19] Sobhani, J., Najimi, M., Pourkhorshidi, A.R, and Parhizkar, T. "Prediction of the compressive strength of no-slump concrete: A comparative study of regression, neural network and ANFIS models". Construction and Building Materials 24 (2010) :709-718. doi:10.1016/j.conbuildmat.2009.10.037.

[20] Özcan, F., Atiş, C.D., Karahan, O., Uncuoğlu, E, and Tanyildizi, H. "Comparison of artificial neural network and fuzzy logic models for prediction of long-term compressive strength of silica fume concrete". Advances in Engineering Software 40(9) (September 2009): 856-863. doi:10.1016/j.advengsoft.2009.01.005.

[21] Raghu Prasad, B.K., Eskandari, H, and Venkatarama Reddy, B.V. "Prediction of compressive strength of SCC and HPC with high volume fly ash using ANN". Construction and Building Materials 23 (January 2009): 117-128. doi:10.1016/j.conbuildmat.2008.01.014.

[22] Abu-Yaman, M., Abd-Elaty, M, and Taman, M. "Predicting the ingredients of self-compacting concrete using artificial neural network". Alexandria Engineering Journal 56 (December 2017): 523–532. doi:10.1016/j.aej.2017.04.007.

[23] Rebouh, R., Boukhatem, B., Ghrici, M, and Hamou, A.T. "A practical hybrid NNGA system for predicting the compressive strength of concrete containing natural pozzolan using an evolutionary structure." Construction and Building Materials 149 (September 2017): 778–789. doi:10.1016/j.conbuildmat.2017.05.165.

[24] Mirza, S.A, and Lacroix, E.A. "Comparative study of strength-computation methods for rectangular reinforced concrete columns." ACI Structural Journal 99 (2002): 399-410.

[25] Tahwia, A.M., Abdelraheem, A.H, and Taha, T. E. "Effect of Silica Fume on Mechanical and Durability Properties of Self-Compacting Concrete". International Journal of Innovative Research in Science, Engineering and Technology 7(5) (May 2018): 6027 – 6039. doi:10.15680/IJIRSET.2018.0705183. .

[26] Dinesh, A., Harini, S., Jasmine Jeba, P., Jincy, J, and Javed, S. "Experimental study on self-compacting concrete". Intern Journ Enginee Scienc Resear Techno 6 (3) (March2017): 42 – 50. doi:10.5281/zenodo.345692.

[27] Syed, A. "Fresh and Mechanical Properties of Self-Consolidating Concrete Incorporating Silica Fume and Metakaolin." Master of Engineering in the Program of Civil Engineering, Toronto, Ontario, Canada. 2009.

[28] Azizifar, Valiollah, and Milad Babajanzadeh. "Compressive Strength Prediction of Self-Compacting Concrete Incorporating Silica Fume Using Artificial Intelligence Methods." Civil Engineering Journal 4, no. 7 (July 30, 2018): 1542. doi:10.28991/cej-0309193.

[29] Nikbin, I.M., Beygi, M. H. A., Kazemi, M. T., Vaseghi Amiri, J., Rabbanifar, S., Rahmani, E, and Rahimi, S. "A comprehensive investigation into the effect of water to cement ratio and powder content on mechanical properties of self-compacting concrete." Construction and Building Materials 57 (April 2014) : 69-80. doi:10.1016/j.conbuildmat.2014.01.098.

[30] Felekoglu, B., Turkel, S, and Baradan, B. "Effect of water/cement ratio on the fresh and hardened properties of self-compacting concrete". Building and environment 42 (April 2007): 1795–1802. doi:10.1016/j.buildenv.2006.01.012.

[31] Hani, N., Nawawy, O., Ragab, K. S, and Kohail, M. "The effect of different water/binder ratio and nano-silica dosage on the fresh and hardened properties of self-compacting concrete." Construction and Building Materials. 165 (March 2018): 504–513. doi:10.1016/j.conbuildmat.2018.01.045.

[32] Gencel, O, C Ozel, W Brostow, and G Martínez-Barrera. "Mechanical Properties of Self-Compacting Concrete Reinforced with Polypropylene Fibres." Materials Research Innovations 15, no. 3 (June 2011): 216–225. doi:10.1179/143307511x13018917925900.

[33] Madandoust, R., Ghavidel, R, and Zadeh, N.N. "Evolutionary design of generalized GMDH-type neural network for prediction of concrete compressive strength using UPV." Computational Materials Science 49(3)(2010):556-567. doi:10.1016/j.commatsci.2010.05.050.

[34] Maage, M. "Strength and Heat Development in Concrete: Influence of Fly Ash and Condensed Silica Fume." CANMET/ACI Fly, Silica Fume Slag Natural Pozzolans Concrete ACI SP 91- 44, 2 (1986): 923-940.

[35] Carette, G.G, and Malhotra, V.M. "Long-term strength development of silica fume concrete." CANMET/ACI Fly, Silica Fume, Slag, Natural Pozzolans Concrete, ACI 132-55 2 (1992): 1017-1044.

[36] Malhotra, V.M. "Mechanical properties and freezing-and-thawing resistance of non-air-entrained and air-entrained condensed silica-fume concrete using ASTM test C 666." procedures A and B D, CANMET/ACI, Fly, Silica Fume, Slag and Natural Pozzolans in Concrete, SP91-53,11 )1986): 1069-1094.

[37] Ahmadi, Babak, and Mohammad Shekarchi. "Use of Natural Zeolite as a Supplementary Cementitious Material." Cement and Concrete Composites 32, no. 2 (February 2010): 134–141. doi:10.1016/j.cemconcomp.2009.10.006.

[38] Chan, S.Y.N, Ji, X. "Comparative study on the initial surface absorption and chloride diffusion of high performance zeolite, silica fume and PFA concretes." Cement and Concrete Composites 21 (August 1999): 293–300. doi:10.1016/S0958-9465(99)00010-4.

[39] Mardani-Aghabaglou, A., Tuyan, M., Yılmaz, G., Arıoz, O, and Ramyar, K. "Effect of different types of superplasticizer on fresh, rheological and strength properties of self-consolidating concrete". Construction and Building Materials 47 (2013) 1020–1025. doi:10.1016/j.conbuildmat.2013.05.105.

[40] Neville, A.M. "Properties of Concrete." 4th Ed., Wiley and Sons, New York, U.S.A 1996.

[41] Benaicha, M., Roguiez, X., Jalbaud, O., Burtschell, Y, and Alaoui, A.H. "Influence of silica fume and viscosity modifying agent on the mechanical and rheological behavior of self-compacting concrete". Construction and Building Materials 84 (March 2015): 103–110. doi:10.1016/j.conbuildmat.2015.03.061.

[42] Wongkeo, W., Thongsanitgarn, P., Ngamjarurojana, A, and Chaipanich, A. "Compressive strength and chloride resistance of self-compacting concrete containing high level fly ash and silica fume." Materials Design. 64 (July 2014): 261–269. doi:10.1016/j.matdes.2014.07.042.

[43] Abib, Z.E, "Formulation and characterization of self-compacting concrete (in French)". MPhil thesis, University of science and technology, Houari Boumediene, Algiers, Algeria. 2004.

[44] Güneyisi, E.,Gesoglu, M,and Özbay, E. "Strength and drying shrinkage properties of self-compacting concretes incorporating multi-system blended mineral admixtures". Construction and Building Materials 24 (April 2010): 1878–1887. doi:10.1016/j.conbuildmat.2010.04.015.

[45] Güneyisi, E., Gesoglu, M. Booya, E, and Mermerdas, K. "Strength and permeability properties of self-compacting concrete with cold bonded fly ash lightweight aggregate". Construction and Building Materials74 (November 2014): 17–24. doi:10.1016/j.conbuildmat.2014.10.032.

[46] Guneyisi, E., Gesoglu, M, and Booya, E. "Fresh properties of self-compacting cold bonded fly ash lightweight aggregate concrete with different mineral admixtures". Materials and Structures. 45 (2012) 1849–59. doi:10.1617/s11527-012-9874-6.

[47] Gesoglu, M., Güneyisi, E, and Özbay, E. "Properties of self-compacting concretes made with binary, ternary, and quaternary cementitious blends of fly ash, blast furnace slag, and silica fume". Construction and Building Materials 23 (November 2008): 1847–1854. doi:10.1016/j.conbuildmat.2008.09.015.

[48] Gesoglu, M, and Ozbay, E. "Effects of mineral admixtures on fresh and hardened properties of self-compacting concretes: binary, ternary and quaternary systems". Materials and Structures 40 (2009): 923–937. doi:10.1617/s11527-007-9242-0.

[49] Abdelgader, H.S., Elbajegni, S.A, and Elwefati, A.M. "Mix designs of self-compacting concrete using local materials "A case study from Libya." Concrete Technology) October 2014): 70–78.

[50] Behfarnia, Kiachehr, and Omid Farshadfar. "The Effects of Pozzolanic Binders and Polypropylene Fibers on Durability of SCC to Magnesium Sulfate Attack." Construction and Building Materials 38 (January 2013): 64–71. doi:10.1016/j.conbuildmat.2012.08.035.

[51] Hassan, Assem A.A., Mohamed Lachemi, and Khandaker M.A. Hossain. "Effect of Metakaolin and Silica Fume on the Durability of Self-Consolidating Concrete." Cement and Concrete Composites 34, no. 6 (July 2012): 801–807. doi:10.1016/j.cemconcomp.2012.02.013.

[52] Sabet, F.A., Libre, N.A, and Shekarchi. M. "Mechanical and durability properties of self-consolidating high performance concrete incorporating natural zeolite, silica fume and fly ash". Construction and Building Materials 44 (April 2013): 175–184. doi:10.1016/j.conbuildmat.2013.02.069.

[53] R'mili, A., Ben-Ouezdou, M., Added, M. and Ghorbel, E. "Prediction of the compressive strengths of self-compacting concrete". Proceedings of International conference, INVACO, Hammamet, Tunisia; 2009. 195-204.

[54] Asteris, Panagiotis G., and Konstantinos G. Kolovos. "Self-Compacting Concrete Strength Prediction Using Surrogate Models." Neural Computing and Applications 31, no. S1 (April 28, 2017): 409–424. doi:10.1007/s00521-017-3007-7.

[55] Safiuddin,Md., Yakhlaf, M, and Soudki, K.A. "Key mechanical properties and microstructure of carbon fibre reinforced self-consolidating concrete." Construction and Building Materials 164 (December 2018): 477–488. doi:10.1016/j.conbuildmat.2017.12.172.

[56] Vivek, S.S., and G. Dhinakaran. "Fresh and Hardened Properties of Binary Blend High Strength Self Compacting Concrete." Engineering Science and Technology, an International Journal 20, no. 3 (June 2017): 1173–1179. doi:10.1016/j.jestch.2017.05.003.

[57] Khodabakhshian, A., Brito, J., Ghalehnovi, M, and Shamsabadi E.A. "Mechanical, environmental and economic performance of structural concrete containing silica fume and marble industry waste powder". Construction and Building Materials. 169 (March 2018): 237–251. doi:10.1016/j.conbuildmat.2018.02.192.

[58] Turk, K., Karatas, M, and Ulucan, Z. C. "Effect of the use of different types and dosages of mineral additions on the bond strength of lap-spliced bars in self-compacting concrete". Materials and Structures 43 (2010): 557–570. doi:10.1617/s11527-009-9511-1

[59] Karatas, Mehmet, Kazim Turk, and Zulfu C. Ulucan. "Investigation of Bond between Lap-Spliced Steel Bar and Self-Compacting Concrete: The Role of Silica Fume." Canadian Journal of Civil Engineering 37, no. 3 (March 2010): 420–428. doi:10.1139/l09-159.

[60] Kennouche, S., Zerizer, A., Benmounah, A., Hami, B., Mahdad, M., Benouali, H,and Bedjou. S. "Formulation and characterization of self-compacting concrete with silica fume". Journal of Engineering and Technology Research 5(5) (June 2013) : 160-169. doi:10.5897/JETR2013.0306.

[61] Zende, Aijaz, and R. B. Khadiranaikar. "Experimental Investigation of High-Strength Self-Compacting Fibre-Reinforced Concrete." Sustainable Construction and Building Materials (December 31, 2018): 345–358. doi:10.1007/978-981-13-3317-0_32.

[62] Gholhaki, M., kheyroddin, A., Hajforoush, M, and Kazemi,M. "An investigation on the fresh and hardened properties of self-compacting concrete incorporating magnetic water with various pozzolanic material". Construction and Building Materials 158 (October 2017): 173–180. doi:10.1016/j.conbuildmat.2017.09.135.

[63] Faez, Azad, Arash Sayari, and Salar Manie. "Mechanical and Rheological Properties of Self-Compacting Concrete Containing Al2O3 Nanoparticles and Silica Fume." Iranian Journal of Science and Technology, Transactions of Civil Engineering 44, no. S1 (January 10, 2020): 217–227. doi:10.1007/s40996-019-00339-y.

[64] Choudhary, Rakesh, Rajesh Gupta, and Ravindra Nagar. "Impact on Fresh, Mechanical, and Microstructural Properties of High Strength Self-Compacting Concrete by Marble Cutting Slurry Waste, Fly Ash, and Silica Fume." Construction and Building Materials 239 (April 2020): 117888. doi:10.1016/j.conbuildmat.2019.117888.

## Appendix I: Data sources

| Author | Year | Ratio W/B | Binder | Silica fume | Fine aggregate | Coarse aggregate | Superplasticizer (SP) | Age (day) | Compressive strength (MPa) |
|---|---|---|---|---|---|---|---|---|---|
| Benaicha et al. [41] | 2015 | 0.37 | 520 | 0 | 890 | 900 | 7.80 | 1 | 29.2 |
| | | 0.37 | 520 | 0 | 890 | 900 | 7.80 | 1 | 29.6 |
| | | 0.37 | 520 | 0 | 890 | 900 | 7.80 | 1 | 30.0 |
| | | 0.37 | 520 | 0 | 890 | 900 | 7.80 | 1 | 28.6 |
| | | 0.37 | 520 | 0 | 890 | 900 | 7.80 | 1 | 29.5 |
| | | 0.37 | 520 | 25 | 890 | 900 | 7.80 | 1 | 35.6 |
| | | 0.37 | 520 | 25 | 890 | 900 | 7.80 | 1 | 34.8 |
| | | 0.37 | 520 | 25 | 890 | 900 | 7.80 | 1 | 34.6 |
| | | 0.37 | 520 | 25 | 890 | 900 | 7.80 | 1 | 34.6 |
| | | 0.37 | 520 | 25 | 890 | 900 | 7.80 | 1 | 34.0 |
| | | 0.37 | 520 | 47 | 890 | 900 | 7.80 | 1 | 32.6 |
| | | 0.37 | 520 | 47 | 890 | 900 | 7.80 | 1 | 32.0 |
| | | 0.37 | 520 | 47 | 890 | 900 | 7.80 | 1 | 32.4 |
| | | 0.37 | 520 | 47 | 890 | 900 | 7.80 | 1 | 32.8 |
| | | 0.37 | 520 | 47 | 890 | 900 | 7.80 | 1 | 32.0 |
| | | 0.37 | 520 | 68 | 890 | 900 | 7.80 | 1 | 32.0 |
| | | 0.37 | 520 | 68 | 890 | 900 | 7.80 | 1 | 31.2 |
| | | 0.37 | 520 | 68 | 890 | 900 | 7.80 | 1 | 31.0 |
| | | 0.37 | 520 | 68 | 890 | 900 | 7.80 | 1 | 30.8 |
| | | 0.37 | 520 | 68 | 890 | 900 | 7.80 | 1 | 31.3 |
| | | 0.37 | 520 | 87 | 890 | 900 | 7.80 | 1 | 31.2 |
| | | 0.37 | 520 | 87 | 890 | 900 | 7.80 | 1 | 30.0 |
| | | 0.37 | 520 | 87 | 890 | 900 | 7.80 | 1 | 30.4 |
| | | 0.37 | 520 | 87 | 890 | 900 | 7.80 | 1 | 32.0 |
| | | 0.37 | 520 | 87 | 890 | 900 | 7.80 | 1 | 29.4 |
| | | 0.37 | 520 | 104 | 890 | 900 | 7.80 | 1 | 30.4 |
| | | 0.37 | 520 | 104 | 890 | 900 | 7.80 | 1 | 30.6 |
| | | 0.37 | 520 | 104 | 890 | 900 | 7.80 | 1 | 29.9 |
| | | 0.37 | 520 | 104 | 890 | 900 | 7.80 | 1 | 30.8 |
| | | 0.37 | 520 | 104 | 890 | 900 | 7.80 | 1 | 30.4 |
| | | 0.37 | 520 | 120 | 890 | 900 | 7.80 | 1 | 30.4 |
| | | 0.37 | 520 | 120 | 890 | 900 | 7.80 | 1 | 30.6 |
| | | 0.37 | 520 | 120 | 890 | 900 | 7.80 | 1 | 29.9 |
| | | 0.37 | 520 | 120 | 890 | 900 | 7.80 | 1 | 30.8 |
| | | 0.37 | 520 | 120 | 890 | 900 | 7.80 | 1 | 30.4 |
| | | 0.37 | 520 | 0 | 890 | 900 | 7.80 | 7 | 33.6 |
| | | 0.37 | 520 | 0 | 890 | 900 | 7.80 | 7 | 34.0 |
| | | 0.37 | 520 | 0 | 890 | 900 | 7.80 | 7 | 33.2 |
| | | 0.37 | 520 | 0 | 890 | 900 | 7.80 | 7 | 32.8 |
| | | 0.37 | 520 | 0 | 890 | 900 | 7.80 | 7 | 33.0 |
| | | 0.37 | 520 | 25 | 890 | 900 | 7.80 | 7 | 44.0 |
| | | 0.37 | 520 | 25 | 890 | 900 | 7.80 | 7 | 44.2 |
| | | 0.37 | 520 | 25 | 890 | 900 | 7.80 | 7 | 46.2 |
| | | 0.37 | 520 | 25 | 890 | 900 | 7.80 | 7 | 44.8 |
| | | 0.37 | 520 | 25 | 890 | 900 | 7.80 | 7 | 44.0 |
| | | 0.37 | 520 | 47 | 890 | 900 | 7.80 | 7 | 45.0 |
| | | 0.37 | 520 | 47 | 890 | 900 | 7.80 | 7 | 45.8 |
| | | 0.37 | 520 | 47 | 890 | 900 | 7.80 | 7 | 45.0 |
| | | 0.37 | 520 | 47 | 890 | 900 | 7.80 | 7 | 45.4 |
| | | 0.37 | 520 | 47 | 890 | 900 | 7.80 | 7 | 45.0 |
| | | 0.37 | 520 | 68 | 890 | 900 | 7.80 | 7 | 46.8 |
| | | 0.37 | 520 | 68 | 890 | 900 | 7.80 | 7 | 46.4 |
| | | 0.37 | 520 | 68 | 890 | 900 | 7.80 | 7 | 48.2 |
| | | 0.37 | 520 | 68 | 890 | 900 | 7.80 | 7 | 48.2 |
| | | 0.37 | 520 | 68 | 890 | 900 | 7.80 | 7 | 49.2 |
| | | 0.37 | 520 | 87 | 890 | 900 | 7.80 | 7 | 49.8 |
| | | 0.37 | 520 | 87 | 890 | 900 | 7.80 | 7 | 49.6 |
| | | 0.37 | 520 | 87 | 890 | 900 | 7.80 | 7 | 49.0 |
| | | 0.37 | 520 | 87 | 890 | 900 | 7.80 | 7 | 49.0 |
| | | 0.37 | 520 | 87 | 890 | 900 | 7.80 | 7 | 48.6 |
| | | 0.37 | 520 | 104 | 890 | 900 | 7.80 | 7 | 50.2 |
| | | 0.37 | 520 | 104 | 890 | 900 | 7.80 | 7 | 48.6 |
| | | 0.37 | 520 | 104 | 890 | 900 | 7.80 | 7 | 48.8 |

| Author | Year | Ratio W/B | Binder | Silica fume | Fine aggregate | Coarse aggregate | Superplasticizer (SP) | Age (day) | Compressive strength (MPa) |
|---|---|---|---|---|---|---|---|---|---|
| | | 0.37 | 520 | 104 | 890 | 900 | 7.80 | 7 | 49.8 |
| | | 0.37 | 520 | 104 | 890 | 900 | 7.80 | 7 | 49.0 |
| | | 0.37 | 520 | 120 | 890 | 900 | 7.80 | 7 | 50.2 |
| | | 0.37 | 520 | 120 | 890 | 900 | 7.80 | 7 | 48.6 |
| | | 0.37 | 520 | 120 | 890 | 900 | 7.80 | 7 | 48.8 |
| | | 0.37 | 520 | 120 | 890 | 900 | 7.80 | 7 | 49.8 |
| | | 0.37 | 520 | 120 | 890 | 900 | 7.80 | 7 | 49.0 |
| | | 0.37 | 520 | 0 | 890 | 900 | 7.80 | 28 | 52.0 |
| | | 0.37 | 520 | 0 | 890 | 900 | 7.80 | 28 | 51.0 |
| | | 0.37 | 520 | 0 | 890 | 900 | 7.80 | 28 | 51.0 |
| | | 0.37 | 520 | 0 | 890 | 900 | 7.80 | 28 | 50.2 |
| | | 0.37 | 520 | 0 | 890 | 900 | 7.80 | 28 | 50.0 |
| | | 0.37 | 520 | 25 | 890 | 900 | 7.80 | 28 | 62.0 |
| | | 0.37 | 520 | 25 | 890 | 900 | 7.80 | 28 | 60.4 |
| | | 0.37 | 520 | 25 | 890 | 900 | 7.80 | 28 | 60.0 |
| | | 0.37 | 520 | 25 | 890 | 900 | 7.80 | 28 | 62.1 |
| | | 0.37 | 520 | 25 | 890 | 900 | 7.80 | 28 | 61.4 |
| | | 0.37 | 520 | 47 | 890 | 900 | 7.80 | 28 | 62.8 |
| | | 0.37 | 520 | 47 | 890 | 900 | 7.80 | 28 | 62.0 |
| | | 0.37 | 520 | 47 | 890 | 900 | 7.80 | 28 | 61.6 |
| | | 0.37 | 520 | 47 | 890 | 900 | 7.80 | 28 | 61.8 |
| | | 0.37 | 520 | 47 | 890 | 900 | 7.80 | 28 | 62.1 |
| | | 0.37 | 520 | 68 | 890 | 900 | 7.80 | 28 | 65.8 |
| | | 0.37 | 520 | 68 | 890 | 900 | 7.80 | 28 | 66.2 |
| | | 0.37 | 520 | 68 | 890 | 900 | 7.80 | 28 | 66.8 |
| | | 0.37 | 520 | 68 | 890 | 900 | 7.80 | 28 | 66.4 |
| | | 0.37 | 520 | 68 | 890 | 900 | 7.80 | 28 | 66.2 |
| | | 0.37 | 520 | 87 | 890 | 900 | 7.80 | 28 | 70.0 |
| | | 0.37 | 520 | 87 | 890 | 900 | 7.80 | 28 | 70.4 |
| | | 0.37 | 520 | 87 | 890 | 900 | 7.80 | 28 | 70.2 |
| | | 0.37 | 520 | 87 | 890 | 900 | 7.80 | 28 | 69.8 |
| | | 0.37 | 520 | 87 | 890 | 900 | 7.80 | 28 | 70.1 |
| | | 0.37 | 520 | 104 | 890 | 900 | 7.80 | 28 | 80.2 |
| | | 0.37 | 520 | 104 | 890 | 900 | 7.80 | 28 | 79.8 |
| | | 0.37 | 520 | 104 | 890 | 900 | 7.80 | 28 | 79.0 |
| | | 0.37 | 520 | 104 | 890 | 900 | 7.80 | 28 | 78.4 |
| | | 0.37 | 520 | 104 | 890 | 900 | 7.80 | 28 | 78.6 |
| | | 0.37 | 520 | 120 | 890 | 900 | 7.80 | 28 | 80.2 |
| | | 0.37 | 520 | 120 | 890 | 900 | 7.80 | 28 | 79.8 |
| | | 0.37 | 520 | 120 | 890 | 900 | 7.80 | 28 | 79.0 |
| | | 0.37 | 520 | 120 | 890 | 900 | 7.80 | 28 | 78.4 |
| | | 0.37 | 520 | 120 | 890 | 900 | 7.80 | 28 | 78.6 |
| Wongkeo et al. [42] | 2014 | 0.30 | 600 | 0 | 1084 | 595 | 7.14 | 3 | 76.0 |
| | | 0.30 | 600 | 30 | 1072 | 595 | 7.98 | 3 | 73.7 |
| | | 0.30 | 600 | 60 | 1059 | 595 | 8.58 | 3 | 78.3 |
| | | 0.35 | 514 | 0 | 1131 | 621 | 8.24 | 3 | 63.4 |
| | | 0.35 | 515 | 26 | 1120 | 621 | 7.71 | 3 | 65.5 |
| | | 0.35 | 515 | 26 | 1120 | 621 | 8.24 | 3 | 63.4 |
| | | 0.35 | 514 | 51 | 1110 | 621 | 9.00 | 3 | 70.8 |
| | | 0.40 | 450 | 0 | 1166 | 640 | 8.10 | 3 | 56.8 |
| | | 0.40 | 451 | 23 | 1157 | 640 | 8.57 | 3 | 55.6 |
| | | 0.40 | 450 | 45 | 1147 | 640 | 9.45 | 3 | 59.8 |
| | | 0.30 | 600 | 0 | 1084 | 595 | 7.14 | 7 | 79.3 |
| | | 0.30 | 600 | 30 | 1072 | 595 | 7.98 | 7 | 81.6 |
| | | 0.30 | 600 | 60 | 1059 | 595 | 8.58 | 7 | 84.5 |
| | | 0.35 | 514 | 0 | 1131 | 621 | 8.24 | 7 | 75.2 |
| | | 0.35 | 515 | 26 | 1120 | 621 | 8.24 | 7 | 77.6 |
| | | 0.35 | 514 | 51 | 1110 | 621 | 9.00 | 7 | 81.2 |
| | | 0.40 | 450 | 0 | 1166 | 640 | 8.10 | 7 | 65.6 |
| | | 0.40 | 451 | 23 | 1157 | 640 | 8.57 | 7 | 65.8 |
| | | 0.30 | 600 | 0 | 1084 | 595 | 7.14 | 28 | 84.0 |
| | | 0.30 | 600 | 30 | 1072 | 595 | 7.98 | 28 | 95.3 |

| Author | Year | Ratio W/B | Binder | Silica fume | Fine aggregate | Coarse aggregate | Superplasticizer (SP) | Age (day) | Compressive strength (MPa) |
|---|---|---|---|---|---|---|---|---|---|
| | | 0.30 | 600 | 60 | 1059 | 595 | 8.58 | 28 | 100.5 |
| | | 0.35 | 514 | 0 | 1131 | 621 | 8.24 | 28 | 83.0 |
| | | 0.35 | 515 | 26 | 1120 | 621 | 8.24 | 28 | 85.3 |
| | | 0.35 | 514 | 51 | 1110 | 621 | 9.00 | 28 | 91.6 |
| | | 0.40 | 450 | 0 | 1166 | 640 | 8.10 | 28 | 72.4 |
| | | 0.40 | 451 | 23 | 1157 | 640 | 8.57 | 28 | 75.3 |
| | | 0.40 | 450 | 45 | 1147 | 640 | 9.45 | 28 | 79.0 |
| | | 0.30 | 600 | 0 | 1084 | 595 | 7.14 | 90 | 88.3 |
| | | 0.30 | 600 | 30 | 1072 | 595 | 7.98 | 90 | 99.0 |
| | | 0.30 | 600 | 60 | 1059 | 595 | 8.58 | 90 | 106.6 |
| | | 0.35 | 514 | 0 | 1131 | 621 | 8.24 | 90 | 85.4 |
| | | 0.35 | 515 | 26 | 1120 | 621 | 8.24 | 90 | 90.9 |
| | | 0.35 | 514 | 51 | 1110 | 621 | 9.00 | 90 | 100.4 |
| | | 0.40 | 450 | 0 | 1166 | 640 | 8.10 | 90 | 80.4 |
| | | 0.40 | 451 | 23 | 1157 | 640 | 8.57 | 90 | 82.4 |
| | | 0.40 | 450 | 45 | 1147 | 640 | 9.45 | 90 | 86.1 |
| Abib [43] | 2004 | 0.38 | 500 | 0 | 794 | 725 | 15.00 | 7 | 34.0 |
| | | 0.40 | 525 | 25 | 794 | 725 | 15.00 | 7 | 36.0 |
| | | 0.40 | 525 | 25 | 794 | 725 | 15.00 | 7 | 36.0 |
| | | 0.36 | 525 | 25 | 794 | 725 | 15.00 | 7 | 40.7 |
| | | 0.32 | 525 | 25 | 794 | 725 | 15.00 | 7 | 42.5 |
| | | 0.36 | 525 | 25 | 794 | 725 | 15.00 | 7 | 40.7 |
| | | 0.36 | 525 | 25 | 794 | 725 | 10.00 | 7 | 43.5 |
| | | 0.36 | 525 | 25 | 794 | 725 | 5.00 | 7 | 40.0 |
| | | 0.40 | 500 | 0 | 794 | 725 | 7.50 | 3 | 28.3 |
| | | 0.40 | 500 | 0 | 794 | 725 | 7.50 | 7 | 35.8 |
| | | 0.40 | 500 | 0 | 794 | 725 | 7.50 | 14 | 43.0 |
| | | 0.40 | 500 | 0 | 794 | 725 | 7.50 | 28 | 45.0 |
| | | 0.40 | 500 | 0 | 794 | 725 | 7.50 | 90 | 49.5 |
| | | 0.36 | 525 | 25 | 794 | 725 | 10.00 | 3 | 32.8 |
| | | 0.36 | 525 | 25 | 794 | 725 | 10.00 | 7 | 39.3 |
| | | 0.36 | 525 | 25 | 794 | 725 | 10.00 | 14 | 48.5 |
| | | 0.36 | 525 | 25 | 794 | 725 | 10.00 | 28 | 56.3 |
| | | 0.36 | 525 | 25 | 794 | 725 | 10.00 | 90 | 60.3 |
| Güneyisi et al. [44] | 2010 | 0.32 | 550 | 0 | 728 | 935 | 8.43 | 28 | 80.9 |
| | | 0.32 | 550 | 28 | 724 | 930 | 9.56 | 28 | 80.4 |
| | | 0.32 | 550 | 55 | 720 | 925 | 10.67 | 28 | 85.7 |
| | | 0.32 | 550 | 83 | 716 | 920 | 12.00 | 28 | 84.4 |
| | | 0.32 | 450 | 23 | 823 | 865 | 4.88 | 28 | 60.7 |
| | | 0.32 | 450 | 45 | 819 | 861 | 5.20 | 28 | 58.5 |
| | | 0.32 | 450 | 68 | 816 | 858 | 7.76 | 28 | 71.1 |
| | | 0.32 | 550 | 28 | 724 | 930 | 9.56 | 90 | 91.1 |
| | | 0.32 | 550 | 55 | 720 | 925 | 10.67 | 90 | 99.2 |
| | | 0.32 | 550 | 83 | 716 | 920 | 12.00 | 90 | 96.7 |
| | | 0.32 | 450 | 23 | 823 | 865 | 4.88 | 90 | 71.2 |
| | | 0.32 | 450 | 45 | 819 | 861 | 5.20 | 90 | 76.1 |
| | | 0.32 | 450 | 68 | 816 | 858 | 7.76 | 90 | 74.8 |
| Güneyisi et al. [45] | 2015 | 0.35 | 550 | 0 | 688 | 688 | 5.50 | 28 | 47.8 |
| | | 0.35 | 550 | 28 | 684 | 684 | 6.40 | 28 | 53.0 |
| | | 0.35 | 550 | 55 | 680 | 680 | 6.40 | 28 | 54.0 |
| | | 0.35 | 550 | 0 | 688 | 688 | 5.50 | 56 | 52.0 |
| | | 0.35 | 550 | 55 | 680 | 680 | 6.40 | 56 | 55.5 |
| | | 0.35 | 550 | 55 | 680 | 680 | 6.40 | 56 | 58.5 |
| Güneyisi et al. [46] | 2012 | 0.35 | 550 | 28 | 684 | 684 | 6.40 | 28 | 53.0 |
| | | 0.35 | 550 | 55 | 680 | 680 | 6.40 | 28 | 54.0 |
| Gesoglu et al. [47] | 2009 | 0.44 | 451 | 23 | 823 | 865 | 4.90 | 28 | 71.2 |
| | | 0.44 | 450 | 45 | 819 | 861 | 5.20 | 28 | 76.1 |
| Gesoglu and Ozbay [48] | 2007 | 0.32 | 550 | 0 | 728 | 935 | 8.53 | 28 | 80.9 |
| | | 0.32 | 550 | 28 | 724 | 930 | 9.56 | 28 | 80.3 |
| | | 0.32 | 550 | 55 | 720 | 925 | 10.67 | 28 | 85.6 |
| | | 0.32 | 550 | 83 | 716 | 920 | 12.00 | 28 | 84.4 |

| Author | Year | Ratio W/B | Binder | Silica fume | Fine aggregate | Coarse aggregate | Superplaciticizer (SP) | Age (day) | Compressive strength (MPa) |
|---|---|---|---|---|---|---|---|---|---|
| Abdelgader et al. [49] | 2014 | 0.38 | 450 | 0 | 918 | 918 | 8.10 | 7 | 30.4 |
| | | 0.40 | 450 | 0 | 903 | 903 | 6.75 | 7 | 24.0 |
| | | 0.45 | 450 | 0 | 873 | 873 | 3.60 | 7 | 32.5 |
| | | 0.38 | 450 | 23 | 925 | 925 | 7.70 | 7 | 28.5 |
| | | 0.40 | 450 | 23 | 911 | 911 | 6.41 | 7 | 33.0 |
| | | 0.42 | 450 | 23 | 897 | 897 | 3.42 | 7 | 33.5 |
| | | 0.45 | 450 | 23 | 882 | 882 | 3.42 | 7 | 29.5 |
| | | 0.38 | 450 | 45 | 933 | 933 | 8.10 | 7 | 21.5 |
| | | 0.40 | 450 | 45 | 920 | 920 | 6.89 | 7 | 28.0 |
| | | 0.42 | 450 | 45 | 906 | 906 | 4.05 | 7 | 30.5 |
| | | 0.45 | 450 | 45 | 893 | 893 | 4.05 | 7 | 26.0 |
| | | 0.38 | 450 | 68 | 939 | 939 | 7.65 | 7 | 22.0 |
| | | 0.40 | 450 | 68 | 927 | 927 | 6.50 | 7 | 29.0 |
| | | 0.42 | 450 | 68 | 914 | 914 | 3.83 | 7 | 33.0 |
| | | 0.45 | 450 | 68 | 901 | 901 | 3.83 | 7 | 27.5 |
| | | 0.38 | 450 | 23 | 925 | 925 | 7.70 | 28 | 45.0 |
| | | 0.38 | 450 | 0 | 918 | 918 | 8.10 | 28 | 43.0 |
| | | 0.40 | 450 | 0 | 903 | 903 | 6.75 | 28 | 39.0 |
| | | 0.42 | 450 | 0 | 888 | 888 | 3.60 | 28 | 40.5 |
| | | 0.45 | 450 | 0 | 873 | 873 | 3.60 | 28 | 41.0 |
| | | 0.40 | 450 | 23 | 911 | 911 | 6.41 | 28 | 44.5 |
| | | 0.42 | 450 | 23 | 897 | 897 | 3.42 | 28 | 46.0 |
| | | 0.45 | 450 | 23 | 882 | 882 | 3.42 | 28 | 44.0 |
| | | 0.38 | 450 | 45 | 933 | 933 | 8.10 | 28 | 42.0 |
| | | 0.40 | 450 | 45 | 920 | 920 | 6.89 | 28 | 49.5 |
| | | 0.42 | 450 | 45 | 906 | 906 | 4.05 | 28 | 50.5 |
| | | 0.45 | 450 | 45 | 893 | 893 | 4.05 | 28 | 46.5 |
| | | 0.40 | 450 | 0 | 903 | 903 | 6.75 | 90 | 52.0 |
| | | 0.42 | 450 | 0 | 888 | 888 | 3.60 | 90 | 54.0 |
| | | 0.45 | 450 | 0 | 873 | 873 | 3.60 | 90 | 49.5 |
| | | 0.38 | 450 | 23 | 925 | 925 | 7.70 | 90 | 56.5 |
| | | 0.40 | 450 | 23 | 911 | 911 | 6.41 | 90 | 55.0 |
| | | 0.45 | 450 | 23 | 882 | 882 | 3.42 | 90 | 52.0 |
| | | 0.38 | 450 | 45 | 933 | 933 | 8.10 | 90 | 59.0 |
| | | 0.40 | 450 | 45 | 920 | 920 | 6.89 | 90 | 56.0 |
| | | 0.42 | 450 | 45 | 906 | 906 | 4.05 | 90 | 57.5 |
| | | 0.45 | 450 | 45 | 893 | 893 | 4.05 | 90 | 54.5 |
| | | 0.38 | 450 | 68 | 939 | 939 | 7.65 | 90 | 64.0 |
| | | 0.40 | 450 | 68 | 927 | 927 | 6.50 | 90 | 62.5 |
| | | 0.45 | 450 | 68 | 901 | 901 | 3.83 | 90 | 60.0 |
| Ahari et al. [4] | (2015) | 0.44 | 455 | 0 | 883 | 783 | 5.75 | 7 | 39.0 |
| | | 0.44 | 455 | 18 | 880 | 778 | 6.70 | 7 | 40.6 |
| | | 0.44 | 455 | 36 | 875 | 774 | 7.50 | 7 | 34.5 |
| | | 0.44 | 455 | 55 | 870 | 771 | 8.00 | 7 | 35.5 |
| | | 0.44 | 455 | 18 | 800 | 778 | 6.70 | 28 | 53.7 |
| | | 0.44 | 455 | 36 | 875 | 774 | 7.50 | 28 | 64.0 |
| | | 0.44 | 455 | 55 | 870 | 771 | 8.00 | 28 | 64.0 |
| | | 0.44 | 455 | 0 | 883 | 783 | 5.75 | 90 | 51.5 |
| | | 0.44 | 455 | 18 | 800 | 778 | 6.70 | 90 | 58.8 |
| | | 0.44 | 455 | 36 | 875 | 774 | 7.50 | 90 | 64.6 |
| | | 0.44 | 455 | 55 | 870 | 771 | 8.00 | 90 | 66.8 |
| Behfarnia,and Farshadfar, [50] | 2013 | 0.38 | 444 | 0 | 1010 | 777 | 5.33 | 28 | 53.8 |
| | | 0.38 | 444 | 22 | 1002 | 777 | 5.33 | 28 | 63.0 |
| | | 0.38 | 444 | 44 | 994 | 777 | 6.66 | 28 | 63.8 |
| | | 0.38 | 444 | 66 | 986 | 777 | 6.66 | 28 | 72.1 |
| | | 0.38 | 444 | 0 | 1010 | 777 | 5.33 | 90 | 57.0 |
| | | 0.38 | 444 | 22 | 1002 | 777 | 5.33 | 90 | 68.0 |
| | | 0.38 | 444 | 44 | 994 | 777 | 6.66 | 90 | 67.0 |
| | | 0.38 | 444 | 66 | 986 | 777 | 6.66 | 90 | 71.5 |
| | | 0.38 | 444 | 0 | 1010 | 777 | 5.33 | 180 | 59.0 |
| | | 0.38 | 444 | 22 | 1002 | 777 | 5.33 | 180 | 71.8 |
| | | 0.38 | 444 | 44 | 994 | 777 | 6.66 | 180 | 75.8 |

| Author | Year | Ratio W/B | Binder | Silica fume | Fine aggregate | Coarse aggregate | Superplasticizer (SP) | Age (day) | Compressive strength (MPa) |
|---|---|---|---|---|---|---|---|---|---|
| | | 0.38 | 444 | 66 | 986 | 777 | 6.66 | 180 | 72.2 |
| | | 0.38 | 444 | 0 | 1010 | 777 | 5.33 | 28 | 63.3 |
| | | 0.38 | 444 | 22 | 1002 | 777 | 5.33 | 270 | 71.5 |
| | | 0.38 | 444 | 44 | 994 | 777 | 6.66 | 270 | 73.8 |
| | | 0.38 | 444 | 66 | 986 | 777 | 6.66 | 270 | 81.5 |
| Bingöl,.and Tohumcu, I [7] | 2013 | 0.35 | 500 | 0 | 967 | 694 | 8.00 | 3 | 61.5 |
| | | 0.35 | 500 | 0 | 967 | 694 | 8.00 | 7 | 75.0 |
| | | 0.35 | 500 | 75 | 948 | 681 | 10.00 | 7 | 79.0 |
| | | 0.35 | 500 | 0 | 967 | 694 | 8.00 | 28 | 78.5 |
| | | 0.35 | 500 | 25 | 958 | 687 | 8.00 | 28 | 78.5 |
| | | 0.35 | 500 | 50 | 954 | 685 | 9.00 | 28 | 82.5 |
| | | 0.35 | 500 | 75 | 948 | 681 | 10.00 | 28 | 87.0 |
| Hassana et al. [51] | 2012 | 0.40 | 450 | 50 | 921 | 891 | 5.83 | 28 | 41.3 |
| | | 0.40 | 450 | 36 | 923 | 893 | 5.40 | 28 | 45.9 |
| | | 0.40 | 450 | 23 | 926 | 896 | 5.15 | 28 | 41.9 |
| | | 0.40 | 450 | 14 | 927 | 898 | 4.55 | 28 | 37.9 |
| Sabet et al. [52] | 2013 | 0.32 | 500 | 100 | 935 | 656 | 12.00 | 3 | 37.0 |
| | | 0.32 | 500 | 50 | 959 | 656 | 9.50 | 28 | 75.0 |
| | | 0.32 | 500 | 100 | 935 | 656 | 12.00 | 28 | 79.5 |
| | | 0.32 | 500 | 50 | 959 | 656 | 9.50 | 90 | 73.0 |
| | | 0.32 | 500 | 100 | 935 | 656 | 12.00 | 90 | 79.5 |
| | | 0.32 | 500 | 50 | 959 | 656 | 9.50 | 180 | 79.5 |
| | | 0.32 | 500 | 100 | 935 | 656 | 12.00 | 180 | 87.0 |
| R'mili et al. [53] | 2009 | 0.40 | 550 | 50 | 790 | 732 | 6.08 | 3 | 30.0 |
| | | 0.38 | 440 | 40 | 906 | 839 | 5.07 | 3 | 24.0 |
| | | 0.42 | 495 | 45 | 849 | 786 | 5.57 | 3 | 26.0 |
| | | 0.37 | 550 | 50 | 791 | 733 | 6.08 | 3 | 30.3 |
| | | 0.51 | 359 | 9 | 1002 | 927 | 2.16 | 7 | 24.0 |
| | | 0.49 | 368 | 18 | 988 | 915 | 3.52 | 7 | 28.0 |
| | | 0.45 | 385 | 35 | 964 | 892 | 4.56 | 7 | 31.5 |
| | | 0.43 | 440 | 40 | 906 | 839 | 5.07 | 7 | 33.0 |
| | | 0.41 | 495 | 45 | 849 | 786 | 5.57 | 7 | 36.0 |
| | | 0.49 | 368 | 18 | 988 | 915 | 3.52 | 28 | 42.5 |
| | | 0.45 | 385 | 35 | 964 | 892 | 4.56 | 28 | 48.5 |
| | | 0.43 | 440 | 40 | 906 | 839 | 5.07 | 28 | 50.0 |
| | | 0.41 | 495 | 45 | 849 | 786 | 5.57 | 28 | 55.5 |
| | | 0.40 | 550 | 50 | 790 | 732 | 6.08 | 28 | 60.3 |
| | | 0.42 | 495 | 45 | 849 | 786 | 5.57 | 28 | 52.5 |
| | | 0.37 | 550 | 50 | 791 | 733 | 6.08 | 28 | 61.0 |
| Asteris and Kolovos [54] | 2017 | 0.33 | 600 | 30 | 900 | 750 | 12.00 | 28 | 80.4 |
| | | 0.32 | 600 | 60 | 900 | 750 | 12.00 | 28 | 79.2 |
| | | 0.35 | 500 | 150 | 900 | 600 | 7.35 | 28 | 48.9 |
| | | 0.35 | 500 | 200 | 900 | 600 | 6.21 | 28 | 42.2 |
| | | 0.35 | 500 | 250 | 900 | 600 | 5.00 | 28 | 35.1 |
| | | 0.44 | 451 | 23 | 823 | 865 | 4.90 | 28 | 71.2 |
| | | 0.44 | 450 | 45 | 819 | 861 | 5.20 | 28 | 76.1 |
| Safiuddin et al. [55] | 2018 | 0.39 | 481 | 48 | 959 | 784 | 7.21 | 3 | 63.4 |
| | | 0.45 | 421 | 42 | 992 | 812 | 4.21 | 3 | 45.5 |
| | | 0.39 | 481 | 48 | 959 | 784 | 7.21 | 7 | 74.5 |
| Vivek et al. [56] | 2017 | 0.40 | 600 | 0 | 810 | 660 | 13.80 | 7 | 35.0 |
| | | 0.40 | 600 | 30 | 810 | 660 | 13.11 | 7 | 34.0 |
| | | 0.40 | 600 | 60 | 810 | 660 | 12.42 | 7 | 32.0 |
| | | 0.40 | 600 | 90 | 810 | 660 | 11.73 | 7 | 31.0 |
| | | 0.40 | 600 | 0 | 810 | 660 | 13.80 | 28 | 63.0 |
| | | 0.40 | 600 | 30 | 810 | 660 | 13.11 | 28 | 60.1 |
| | | 0.40 | 600 | 60 | 810 | 660 | 12.42 | 28 | 58.1 |
| | | 0.40 | 600 | 90 | 810 | 660 | 11.73 | 28 | 55.3 |
| | | 0.40 | 600 | 120 | 810 | 660 | 11.04 | 28 | 51.4 |
| | | 0.40 | 600 | 150 | 810 | 660 | 10.35 | 28 | 45.1 |
| Khodabakhshian et al. [57] | 2018 | 0.45 | 400 | 0 | 793 | 1000 | 1.30 | 7 | 46.0 |
| | | 0.45 | 400 | 10 | 791 | 1000 | 1.45 | 7 | 48.0 |
| | | 0.45 | 400 | 20 | 788 | 1000 | 1.45 | 7 | 48.0 |

| Author | Year | Ratio W/B | Binder | Silica fume | Fine aggregate | Coarse aggregate | Superplasticizer (SP) | Age (day) | Compressive strength (MPa) |
|---|---|---|---|---|---|---|---|---|---|
| | | 0.45 | 400 | 10 | 791 | 1000 | 1.45 | 28 | 59.0 |
| | | 0.45 | 400 | 20 | 788 | 1000 | 1.45 | 28 | 60.0 |
| | | 0.45 | 400 | 40 | 784 | 1000 | 1.60 | 28 | 66.0 |
| | | 0.45 | 400 | 0 | 793 | 1000 | 1.30 | 56 | 55.0 |
| | | 0.45 | 400 | 10 | 791 | 1000 | 1.45 | 56 | 65.0 |
| | | 0.45 | 400 | 20 | 788 | 1000 | 1.45 | 56 | 66.0 |
| | | 0.45 | 400 | 40 | 784 | 1000 | 1.60 | 56 | 68.0 |
| | | 0.45 | 400 | 0 | 793 | 1000 | 1.30 | 90 | 60.0 |
| | | 0.45 | 400 | 10 | 791 | 1000 | 1.45 | 90 | 68.0 |
| | | 0.45 | 400 | 20 | 788 | 1000 | 1.45 | 90 | 71.0 |
| | | 0.45 | 400 | 40 | 784 | 1000 | 1.60 | 90 | 74.0 |
| | | 0.45 | 400 | 0 | 793 | 1000 | 1.30 | 180 | 62.0 |
| | | 0.45 | 400 | 10 | 791 | 1000 | 1.45 | 180 | 71.0 |
| | | 0.45 | 400 | 20 | 788 | 1000 | 1.45 | 180 | 73.0 |
| | | 0.45 | 400 | 40 | 784 | 1000 | 1.60 | 180 | 77.0 |
| Turk et al. [58] | 2010 | 0.36 | 450 | 23 | 990 | 735 | 8.00 | 3 | 36.2 |
| | | 0.38 | 450 | 45 | 990 | 735 | 8.00 | 3 | 33.2 |
| | | 0.40 | 450 | 68 | 990 | 735 | 8.00 | 3 | 30.9 |
| | | 0.40 | 450 | 90 | 990 | 735 | 8.00 | 3 | 31.3 |
| | | 0.36 | 450 | 23 | 990 | 735 | 8.00 | 7 | 43.9 |
| | | 0.38 | 450 | 45 | 990 | 735 | 8.00 | 7 | 47.0 |
| | | 0.40 | 450 | 68 | 990 | 735 | 8.00 | 7 | 40.9 |
| | | 0.40 | 450 | 90 | 990 | 735 | 8.00 | 7 | 40.4 |
| | | 0.36 | 450 | 23 | 990 | 735 | 8.00 | 28 | 58.0 |
| | | 0.38 | 450 | 45 | 990 | 735 | 8.00 | 28 | 62.8 |
| | | 0.40 | 450 | 68 | 990 | 735 | 8.00 | 28 | 68.0 |
| | | 0.40 | 450 | 90 | 990 | 735 | 8.00 | 28 | 66.4 |
| Karatas et al. [59] | 2010 | 0.36 | 450 | 23 | 932 | 793 | 8.00 | 28 | 36.5 |
| | | 0.38 | 450 | 45 | 932 | 793 | 8.00 | 28 | 44.1 |
| Kennouche et al. [60] | 2013 | 0.42 | 460 | 60 | 827 | 798 | 7.20 | 7 | 22.0 |
| | | 0.42 | 460 | 60 | 827 | 799 | 6.00 | 7 | 25.0 |
| | | 0.42 | 460 | 60 | 785 | 798 | 8.00 | 7 | 27.5 |
| | | 0.42 | 460 | 60 | 827 | 798 | 7.20 | 14 | 31.0 |
| | | 0.42 | 460 | 60 | 827 | 799 | 6.00 | 14 | 41.0 |
| | | 0.42 | 460 | 60 | 785 | 798 | 8.00 | 14 | 33.5 |
| | | 0.42 | 460 | 60 | 827 | 798 | 7.20 | 28 | 40.0 |
| | | 0.42 | 460 | 60 | 827 | 799 | 6.00 | 28 | 43.5 |
| | | 0.42 | 460 | 60 | 785 | 798 | 8.00 | 28 | 41.5 |
| Zende, and Khadiranaikar [61] | 2019 | 0.26 | 575 | 86 | 833 | 700 | 2.93 | 7 | 43.8 |
| | | 0.24 | 575 | 86 | 833 | 700 | 3.42 | 7 | 47.2 |
| | | 0.22 | 575 | 86 | 833 | 700 | 3.81 | 7 | 51.0 |
| | | 0.26 | 575 | 86 | 833 | 700 | 2.93 | 28 | 55.1 |
| | | 0.24 | 575 | 86 | 833 | 700 | 3.42 | 28 | 60.0 |
| Gholhaki et al. [62] | 2018 | 0.37 | 400 | 40 | 1069 | 766 | 3.45 | 7 | 38.0 |
| | | 0.37 | 400 | 80 | 1062 | 761 | 5.37 | 7 | 40.0 |
| | | 0.37 | 400 | 0 | 1085 | 778 | 5.75 | 28 | 38.0 |
| | | 0.37 | 400 | 40 | 1069 | 766 | 3.45 | 28 | 54.0 |
| | | 0.37 | 400 | 80 | 1062 | 761 | 5.37 | 28 | 57.5 |
| Faez et al. [63] | 2019 | 0.44 | 385 | 35 | 960 | 920 | 2.76 | 7 | 21.1 |
| | | 0.44 | 385 | 35 | 960 | 920 | 2.76 | 28 | 26.1 |
| | | 0.44 | 385 | 35 | 960 | 920 | 2.76 | 90 | 29.3 |
| Choudhary et al. [64] | 2020 | 0.33 | 550 | 0 | 970 | 722 | 7.70 | 7 | 39.1 |
| | | 0.33 | 550 | 28 | 970 | 722 | 8.25 | 7 | 44.1 |
| | | 0.33 | 550 | 28 | 970 | 722 | 8.25 | 28 | 58.2 |
| | | 0.33 | 550 | 0 | 970 | 722 | 7.70 | 90 | 56.8 |
| | | 0.33 | 550 | 28 | 970 | 722 | 8.25 | 90 | 59.9 |